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Impact of Emerging Water Scenarios on Performance of Urban Water Networks

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Impact of Emerging Water Scenarios on Performance of Urban Water Networks

by

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Abstract

Impact of Emerging Water Scenarios on Performance of Urban Water Networks

by

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The University of Texas at Austin, 2018

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Concerns over the impacts of urban growth have prompted the development and adoption of water-demand management strategies. Water and energy savings from increasingly efficient technologies, diversified water sources, and water savings policies are typically quantified from an individual demand-side basis, but network-wide potential is not well studied. This paper studies the effects of residential demand profiles on the performance of urban water networks, in response to emerging demand management strategies. To assess the performance of three demand scenarios: 1) base, 2) conservation, and 3) load-shifting, hydraulic simulations were conducted. Four metrics of network performance are suggested to evaluate responses to scenarios: water loss, water age, energy loss, and peak flow. The results revealed network performance for energy and flow metrics improved under both conservation and load-shifting scenarios. However, these scenarios had either a negative or an insignificant impact on water age and losses throughout the network. The results indicate potential savings from these demand profiles cannot be fully realized without adjustments in network operation, and may come at a cost in terms of water quality. This works suggests an initial tool for evaluating network-wide effects of different demand management strategies.

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Chapter 1: Introduction

Urban water networks (UWNs) are the backbone of water provision in environments from small municipalities to megacities. Public utilities are responsible for providing safe drinking water in adequate quantities with sufficient pressure at economical rates, while minimizing losses and maintaining reliable service. The urban water sector faces mounting challenges in providing for continuously growing populations worldwide. Population growth and increasing water demand is outpacing infrastructure renewal and expansion. In 2016, 54% of the the world's population, lived in cities, and by mid-century, the urban population is projected to surpass six billion (United Nations, 2014). Currently, in the United States, there are about 155,000 public drinking water systems (US EPA, 2008a), which serve approximately 95% of the total population (US EPA, 2017). Well-developed urban centers with existing water infrastructure are also susceptible to inadequate drinking water provisions and associated public health risks (Maxmen, 2018, Rhoads et al., 2017). Other urban demand considerations include temporary influxes of people, shrinking cities, infrastructure deterioration, funding availability, and demand-supply uncertainty, all of which exacerbate challenges to meet future demands. To address current and projected needs, the water sector requires a significant investment nationwide of $384.2 billion (US EPA, 2009) to replace, maintain, and expand service.

The pervasiveness of outdated infrastructure supports the need to study how changes in consumer consumption behavior affects the UWN. Despite overall population and demand growth, daily residential indoor water usage per U.S. household has decreased 22% over the last two decades (DeOreo et al., 2016). Water use for clothes washers, toilets, and dishwashers saw the biggest reduction per capita due to efficiency (DeOreo et al., 2016). U.S. water conservation efforts focus largely on the consumer-side, with 68% of utilities sponsoring active conservation programs (AWWA, 2017). A combination of water savings tools have indeed contributed to curbing demand per capita (Gregg et al., 2007). Examples of promoted conservation tools include installing water efficient fixtures (Mayer et al., 2000), smart meters to inform consumer usage (Marchment Hill Consulting, 2010), and diversifying water supply sources such as greywater reuse and rainwater harvesting (Larsen et al., 2016).

The outcome of most consumer-side demand management (DM) strategies, such as technological, price-based, and policy approaches, is primarily dependent on short and long-term user response. An example of a technological strategy is the advancement and adoption of water-efficient appliances as indoor or outdoor fixture retrofits. Higher efficiency appliances result in indoor water savings for the consumer (Carragher et al., 2012). Certain retrofits may impact usage patterns since high-volume indoor fixtures influence total daily household demand, while outdoor water use drives peak demands (Beal and Stewart, 2014). Alternative, decentralized supply sources such as rainwater harvesting, greywater systems, stormwater collection, and air-conditioning condensation can supplement or replace withdrawal from the UWN for outdoor uses (Larsen et al., 2016), but high initial costs may hinder widespread implementation (Malinowski et al., 2015). There is substantial demand reduction potential for residential as well as non-residential sectors: 30% of residential water use in the United states is allocated to irrigation (US EPA, a), and indoor water use rates for commercial users are up to 10 times greater than residential ones (Morales et al., 2013). A combination of more water-efficient indoor devices and better irrigation practices achieves maximum demand reduction across water use sectors, as well as decreased energy utilization for the consumer (Friedman et al., 2014). In a real-world UWN, this combination effectively minimizes fluctuations and reduces overall demand, but curtails dependence on water supplied from the utility (Gurung et al., 2015). An analysis of indoor and outdoor DM with water-energy-carbon modeling revealed reductions in water footprint, energy use, and carbon emissions for a real-world network (Chhipi-Shrestha et al., 2017).

Studies show that water efficient end-use devices positively affect indoor water savings (Mayer et al., 2004). Upgrading to higher-efficiency appliances achieved water savings of 27-80% depending on the appliance (Mayer et al., 2004), and implies accompanying energy savings due to water heating (US EPA, 2008b). Rainwater harvesting technologies reportedly provide potential water savings ranging between 8-44% (Steffen et al., 2013), and greywater reuse could yield greater savings (Zhang et al., 2009). While some studies show potential savings for water utilities (Malinowski et al., 2015, Chhipi-Shrestha et al., 2017), others report energy costs to the consumer (Racoviceanu and Karney, 2010) and question the feasibility at the residential level (Gregg et al., 2007, Yu et al., 2013). On a higher level, state and local governments aim to save a specific amount to reduce stress on existing resources and delay costs. For example, in an effort to achieve a 5% reduction for daily water use per capita, an utility in Austin, Texas, offered subsidies and rebates for rainwater collection, among other strategies, estimating savings of 49,177 gpd over five years (Gregg et al., 2007).

Policy-based approaches regulate water use, typically for conservation purposes. The success of policies, which include rebates, legislative mandates, and changing water rates, are affected by economic development, environmental settings, and agency operation (Maggioni, 2015). Mandatory conservation regulation positively impacts water usage reduction per capita, but the effects of water pricing and subsidies are not significant (Maggioni, 2015). Despite the relative inelasticity of water pricing, some studies argue price-based strategies are more cost-effective and enforceable than other conservation strategies, such as restricting outdoor irrigation (Olmstead and Stavins, 2007). Due to increased concerns over water availability in the future, it is likely that current and new methods of DM will endure.

Demand management on the utility-side includes demand estimation, smart metering, and water loss control. Utilities implement water loss control to assess and reduce leakage. Water loss control by the utility is implemented to assess and reduce leakage. The major components of a water-loss control program an assessment of real and hidden losses through audits, as well as implementation of leakage control measures. Control measures such as establishing district-metered areas and pressure management can extend the life of existing infrastructure by reducing zone pressure, minimizing pipe failure, and decreasing consumption in the network while cutting down on losses (Wright et al., 2015, Ulanicki et al., 2008). Some argue that utility-side measures are more effective than consumer-side DM for water conservation (Sturm and Thornton, 2007).

Smart metering has aided in the advocacy of consumer-oriented demand management due to the high spatial and temporal resolution of the data. Disaggregating high-resolution data for water end-use characterizations is useful for studying the effects of water-efficient devices and user consumption profiles (Mayer et al., 2000). Adoption of end-use tools and identification of corresponding water use patterns has notable implications for water demand modeling and infrastructure planning (Gurung et al., 2015). The advancement of water demand modeling using smart metered data may also be useful for consumer-side applications so that a utility can make intelligent operation and planning decisions in response to changes in demand (Nguyen et al., 2018). Moreover, smart metering methodologies and tools have the potential to provide a more integrated approach to the four phases of residential demand management: data gathering, characterizing end-uses, demand modeling, and design and implementation (Cominola et al., 2015). Demand profiles (DPs) are typically developed using historical trends. The effects of rapid adoption of technologies and policies may not be seen immediately in these trends. Therefore, there is a missed opportunity if consumer profiles evolve faster than a utility's operational response.

To the author's knowledge, the literature has only briefly addressed the impacts of consumer-side DM on certain aspects of network performance. Hydraulic models with DPs reflecting water efficiency, rainwater harvesting, and greywater systems suggested increased infrastructure life and capital cost savings for existing UWNs (Gurung et al., 2016). Life-cycle methodology applied to DM scenarios estimated energy use and GHG emissions (Racoviceanu and Karney, 2010). Water savings scenarios have also been used to examine the effect of decentralized water supplies on water quality performance (Sitzenfrei et al., 2017). Decentralized sources offer the capability to supplement consumption from the public UWN, thereby introducing the possibility of decreased velocities in the network. Low velocities increase detention times, which can impact effectiveness of corrosion control, as well as create areas of stagnation and sediment deposition (National Research Council, 2015).

Understanding the relationship between DM strategies, network performance, and actual potential savings for utilities can strengthen the case for quicker and widespread implementation of demand management, or advise decision makers about how to capitalize on changing water usage behaviors. This work studies the network-wide effects of demand management to support decision making on the utility-side. Three scenarios, representing baseline and emerging consumer behavior due to DM, are considered in this analysis with the following objectives:

1. Establish the profiles of a 1) baseline and two emerging demand scenarios: 2) conservation, and 3) load-shifting.

2. Suggest four metrics for evaluating network performance: water loss, water age, energy loss, and peak flow.

3. Analyze impacts of emerging demand scenarios on a benchmark network and

additional UWNs in comparison to the baseline.

This paper is structured as follows: Chapter 2 describes the methodology for selecting water demand profiles and suggested performance metrics; Chapter 3 provides a detailed system study on the results from hydraulic simulations of a benchmark urban water network; Chapter 4 analyzes the network performance results of additional UWNs under the chosen demand scenarios; and Chapter 5 discusses the implications of this study and future work.

Chapter 2: Methods

To study the effects of consumer behavioral changes on network performance, water demand scenarios of interest were chosen: 1) base, 2) conservation, and 3) load-shifting. These scenarios reflect changes by residential users in response to water saving and demand management strategies. To evaluate performance, scenario-specific demand profiles (DPs) were applied to network simulations. This study suggests four metrics to assess network performance results: water loss, water age, energy loss, and peak flow.

2.1 WATER DEMAND SCENARIOS

Changes in DPs reflect consumer behavior, which may be affected by access to more efficient technology, alternative water sources, and demand response policies. Three scenarios were studied: 1) a base case representing typical, diurnal residential behavior, 2) conservation, in response to water saving measures, and 3) load-shifting, where there is no variability in demand. Each scenario has a corresponding DP used in the simulations. Extreme DPs were used to illustrate the direction of emerging demand scenarios and maximum possible savings. A demand profile is a series of multipliers that scale the base demands of consumers, such that a value of 0.5 would cut the demand in half. Figure 2.1 plots the demand multipliers of the DP for each scenario over a 24-hour time period. Deriving profiles from metered data or through modeling is beyond the scope of this project.

2.1.1 Scenario S0 (Base)

Typical residential water demand varies throughout the day and peaks twice, during the morning and late evening hours. Outdoor water use, such as irrigation on automatic timers, as well as indoor activity at the beginning and end of the day, including washing, cooking, etc, are drivers of demand peaks for residential households (Funk and DeOreo, 2011). The water demand peaks may coincide with those of the electricity load curve, which also exhibits a morning ramp and evening peak (U.S. Energy Information Administration, 2011) because of energy uses, such as water heating (Bouchelle et al., 2000, Parker, 2002). The timing and shape of peaks in

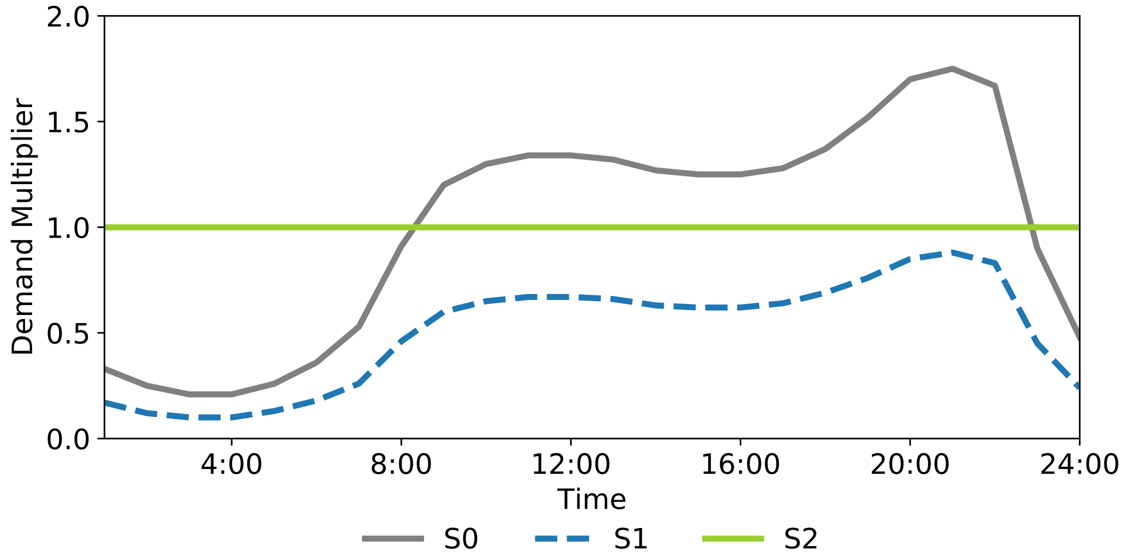


Figure 2.1: Daily residential demand profiles for base (S0), conservation (S1), and load-shifting (S2) scenarios.

residential water DPs are dependent on the local characteristics of climate, weather, and demographics (Rothstein, 1992, DeOreo et al., 2016), but typically still follows a diurnal pattern (National Research Council, 2015).

Scenario S0 serves as the baseline, where there is no change in residential water demand behavior. Therefore, the DP follows diurnal residential demand. The standard, average-day flow curve, developed by the American Water Works Association (AWWA, 1989) was used as the profile for the base scenario, as shown in Figure 2.1.

2.1.2 Scenario S1 (Conservation)

In the conservation scenario, overall consumption is reduced in response to advances in end-user technology, such as efficient appliances and decentralized supply systems. The conservation scenario represents an ambitious and extensive adoption of demand management technologies. The DP was based on smart-metered data collected in a study of residential households equipped with some combination of alternative water sources and efficient appliances (Gurung et al., 2015). Where households had access to water efficient technology, rainwater harvesting, and greywater systems, peak demands decreased by 52% and 64% on average and peak days, respectively (Gurung et al., 2015). Source substitution for outdoor water use curbed peak demands on the average day, while further reduction was realized through efficient appliances for indoor purposes (Gurung et al., 2015). Consumer-side DM has the potential to reduce indoor and outdoor use by up to 50% and 40%, respectively (Mayer et al., 2004, Steffen et al., 2013). Another study used DPs reduced to 50-60% of the base after modeling a 44-54% decrease in residential demand from water savings scenarios (Racoviceanu and Karney, 2010). The conservation DP exhibits a reduced overall demand and lowered peaks. Thus, to generate these changes, the base DP was uniformly reduced by 50%, as shown in Figure 2.1, such that the total daily demand, D, was 50% less than that of the base scenario.

2.1.3 Scenario S2 (Load-shifting)

The load-shifting scenario represents a redistribution of hourly demands throughout the day while the total daily water consumption remains the same. Redistribution may occur through the adoption of DM such as conservation rules, economic incentives, and decentralized supply systems or local storage. For example, households fitted with a rainwater tank may replenish their onsite supply overnight, off-peak hours, from the public water network in order to help meet demands during the daytime. The resulting DP exhibited higher-than-normal demands overnight and dampened peaks (Gurung et al., 2015). Some of the households' water demand load was effectively shifted from high usage times to off-peak.

Load-shifting is common practice in the energy industry to shave peak demands. An application of this is remotely controlling customers' air-conditioning during peak demands when needed as a means of addressing generation capacity limitations. In the residential sector, some utilities employed a similar strategy to shift timing of water use off peak energy demand periods in the residential water sector with remote-controlled irrigation (Mayer and Smith, 2017, House and House, 2012).

Variable DPs produce fluctuations in flows and pressures that may re-suspend microbes or sediment, compromise hydraulic integrity, and accelerate pipe material failure due to stress (US EPA and WRF, 2010, National Research Council, 2015). Transitions in pumping, tank levels, and valve opening in response to demand needs lead to changes in velocities and pressure loading (National Research Council, 2015), which in turn affects the life of existing infrastructure, water losses, and associated capital costs (Rezaei et al., 2015). Thus, performance results under a load-shifting scenario are insightful.

An extreme case of load-shifting could create a non-variable demand throughout the day. Evidence shows that this non-variability could be achieved, but investigation into the specifics is beyond the scope of this study. The load-shifting DP is a horizontal line derived from the base by taking the average of the demand multipliers across the entire time period so that there is no change in the total daily demand, D. In this study, the demand multiplier is held at 1.0 across all times, as seen in Figure 2.1.

2.2 HYDRAULIC SIMULATIONS

After deriving the demand profiles, the scenarios were employed in simulations of hydraulic networks. Hydraulic modeling of water networks aids in planning, design, and operation. Model results can also reveal deficiencies and identify areas in need of improvement (National Research Council, 2015). In the hydraulic simulations, the conservation of mass was satisfied such that the inflows and outflows were balanced. Based on the conservation of mass, the flow at any junction is as follows:

$$Q_{ext,i} = \sum_{k \in Jin} Q_k - \sum_{k \in Jout} Q_k \tag{2.1}$$

where $Q_{ext,i}$ is the external demand at junction i, and Q_k is the flow in pipe k in the set of pipes Jin or $Jout$, contributing to or leading out of the node, respectively. The conservation of energy is also observed between any two points, A and B:

$$H_A - H_B = \sum_{k \in Jpath} {\scriptstyle (+/-)} K_k |Q_k|^n \tag{2.2}$$

where H_A and H_B are the total heads at incident nodes A and B, K_k and Q_k are the Hazen-Williams head loss coefficient and flow of pipe k from the set in the path $Jpath$, $n = 1.85$ for Hazen-Williams, and ${\scriptstyle (+/-)}$ is the sign from Q_k indicating flow direction. The flow continuity and head loss equations are solved iteratively as a system of nonlinear equations using the Newton-Raphson method (Boulos et al., 2006).

Hydraulic and water quality analyses for all scenarios were conducted using EPANET2 (Rossman, 2000) and a Python wrapper (Pathirana, 2016). EPANET2 performs extended-period hydraulic and water quality analysis with demand-driven modeling. The water quality analysis uses the principles of conservation of mass and reaction kinetics. Simulations of the three demand scenarios were run with UWNs of various sizes and configurations. The extended-period simulations ran for 24 hours with the following time steps: 30-minute hydraulic, 5-minute water quality, and 1-hour pattern. The UWN models were not modified. Due to limited data availability, this study assumed all users in a UWN were strictly residential households.

2.3 METRICS FOR NETWORK PERFORMANCE

This study suggests four performance metrics to evaluate the network under different demand scenarios: water loss, peak flow, water age, and energy loss. Similar indicies were used to evaluate energy efficiency in water supply (Pelli and Hitz, 2000) and impacts of conservation strategies (Chhipi-Shrestha et al., 2017, Malinowski et al., 2015, Sitzenfrei et al., 2017). The metrics were calculated using data from hydraulic and water quality simulations (Rossman, 2000). In this study, residential users were nodes with a non-zero demand, and referred to as junctions.

2.3.1 Water Loss

Water loss in a network consists of real and hidden losses. Real losses include background leakage, pipe bursts, and theft. Background leakage in UWNs can result in significant water loss because it occurs continuously in low volumes over time. Distribution networks in the United States experience an average water loss of 16% (US EPA, 2013). Aging infrastructure leads to increased water loss due to more frequent pipe failure and background leakage (Rezaei et al., 2015). Elevated costs on the consumer-side are associated with maintenance, loss control measures, and added water supply. Additional water must be pumped, treated, and conveyed to make up for the loss, which consequently effects energy consumption by the utility (Plappally and Lienhard, 2012). Economic and environmental costs stemming from leakage as well as loss control efforts are of concern for both water utilities and residential consumers alike. The amount of leakage from a system is related to pressure (Vicente et al., 2016, May, 1994, van Zyl, 2014). Therefore, decreased volume and fluctuations in demand may reduce water losses in the network.

To estimate background leakage, we adapted the approach by Giustolisi et al.

(2008), in which water loss at the node is evaluated as the sum of all contributing incident pipes:

$$q_i = \frac{1}{2}\sum_{k=1}^{m} \beta L p^{\alpha} \tag{2.3}$$

where q_i represents the water loss at junction i, and is calculated from the leakage in the incident pipes k for $k = 1, 2, ...m$. The pipe leakage is a function of the length L, pressure p, as well as leakage parameters β and α. Leakage model parameter, β is dependent on pipe characteristics, as well as environmental factors such as corrosion, loading, and stress, while α is only dependent on pipe material and rigidity. An α value of 1.5 is typically used for background losses regardless of pipe material (May, 1994, Lambert, 2001). Parameter β is an empirical constant calibrated to the network (Giustolisi et al., 2008). However, an estimated value of $\beta = 10^{-7}$ was used since this study was assessing differences among demand scenarios on the same network rather than quantifying losses. Typical values of β range in magnitude from 10^{-4} to 10^{-10} depending on various network characteristics (Maskit and Ostfeld, 2014, Berardi et al., 2015). To compute total background leakage in the network for the water loss metric, I_w, the individual leak values from equation (2.3) were summed over the entire time period.

2.3.2 Water Age

Along with delivering sufficient flows, supplying water of adequate quality is an essential service provided by utilities. Water age is a reliable indicator of water quality in the network (Walksi et al., 1989). Low flows, as a result of conservation measures, may influence water quality in supply networks (US EPA, 2002). Increased age can have potential health impacts relating to the exposure of waterborne pathogens in addition to affecting aesthetic properties such as taste, color, and temperature (US EPA, 2002). In EPANET2, water age is modeled at the junctions as a zero-order reaction with a rate constant of 1 (Rossman, 2000). Therefore, upon entering the network through source nodes at zero, the water age increases one hour with every hour that passes. For the water age metric, I_a we used the *median* water age in the network at the final time step. In this study, the age was taken at the end of 24 hours.

2.3.3 Energy Loss

The delivery of both energy and water services are linked. In the United States, 30-40% of energy consumption in a municipality is attributed to water and wastewater utilities (US EPA, b). A water utility's energy consumption accounts for 5-30% of its total operating costs (World Bank, 2012). Therefore, a utility's energy usage can have substantial financial impacts. The primary source of energy use, accounting for 55-90%, in a UWN is pumping raw and treated water to meet user demand and maintain adequate pressure and flow in the network (Pabi et al., 2013). Energy consumption in the utility is influenced by the size of the system and topology of the location (Plappally and Lienhard, 2012, Pelli and Hitz, 2000). Changes in DPs may impact pumping volume, scheduling, and the energy rates charged to a water utility. Therefore, energy loss due to friction was chosen to examine energy costs in the network. Friction is the major source of hydraulic energy loss in pipe flow. Head losses in the pipes, which include friction and minor losses, are representative of energy losses in the network because the pumps must work to compensate for these losses. Since water loss in the network also requires increased pumping, the cost of water and energy losses for utilities are linked. For ease in analysis, the head losses in pipes, computed using the Hazen-Williams formulation (Rossman, 2000), were assigned to the incident nodes, such that there was no difference between total head loss in pipes versus nodes. The energy loss metric, I_e, was then computed by summing the head losses in all nodes over the entire simulation period.

2.3.4 Peak Flow

Water utilities must continue to deliver water while facing challenges due to aging infrastructuresuch as funding necessary pipe upgrades and replacement. Pipes may require upgrades or replacement. Peak flows, along with peak-day and average-day demand, are critical design considerations for engineers and planners to determine pipe capacities (Beal and Stewart, 2014). Long term changes in peak demands due to emerging behavior profiles can affect sizing of new mains as well as the timing and necessity of network augmentations (Gurung et al., 2016). The peak flow metric, I_f, was obtained by taking the *median* of a distribution of maximum flow rates in all pipes.

Chapter 3: Benchmark Network Analysis

A detailed study on the hydraulic simulations of a benchmark UWN, Net 4, is presented in this chapter, starting with an analysis of pressures and flows, then followed by network performance and a comparison of the results among the three scenarios. Net 4 has 964 nodes, 1156 pipes consisting of approximately $854 \times 10^3 ft$, two pumps, four tanks, and one source. A graph of Net 4, as seen in Figure 3.1, shows the topology of the real-world network. The UWN serves 1.51 million gallons of water daily to a population of 19,320 (Jolly et al., 2014). For this analysis, the symbol Δ is defined as the difference between two values, $I'_{i/k} - I^o_{i/k}$, where $I'_{i/k}$ and $I^o_{i/k}$ are metric values of interest for individual features (nodes i or pipes k) from the emerging (S1 or S2) and base (S0) scenarios, respectively. In order to remove outliers due to idiosyncrasies in demand-driven modeling, only the central 95% of the results distribution over time for any node or pipe was used in this paper.

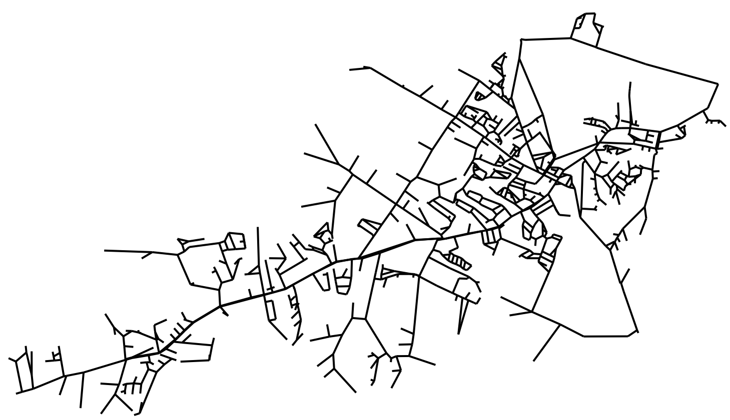
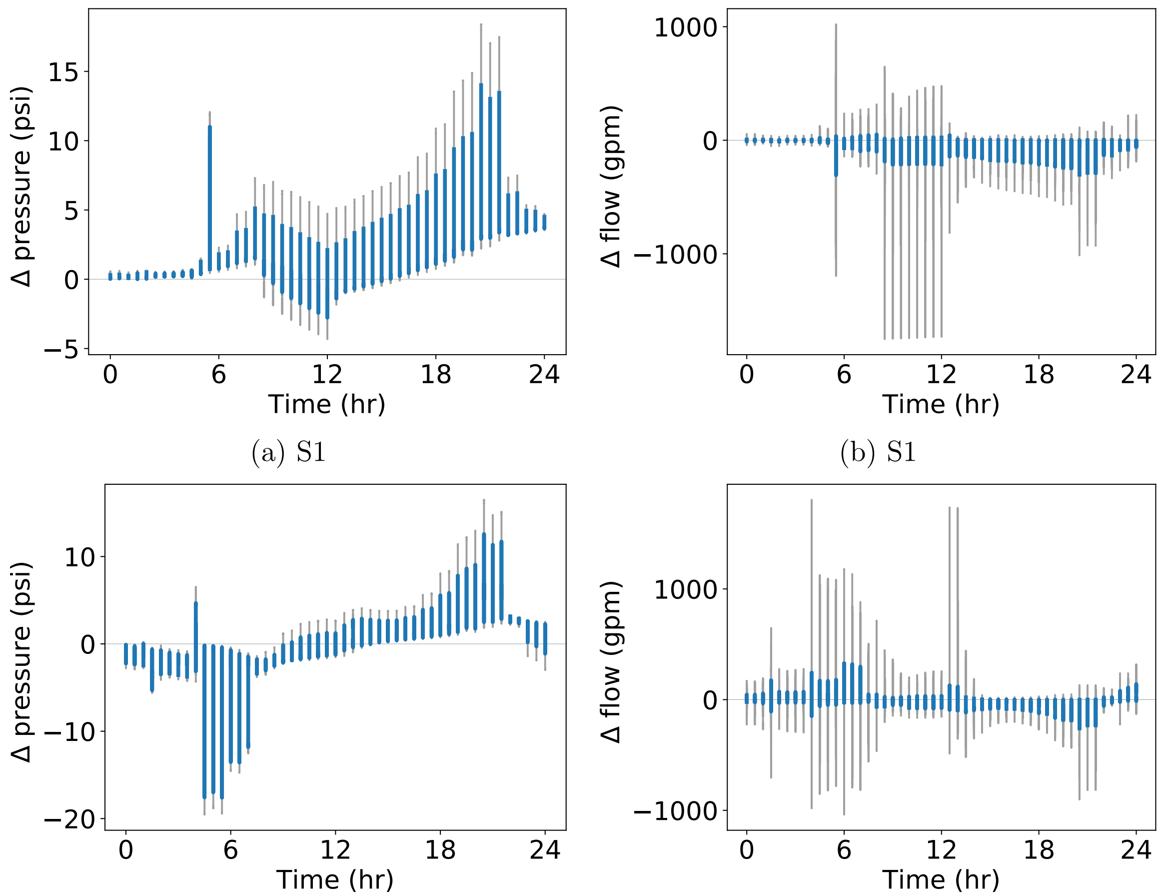


Figure 3.1: Topology of benchmark network, Net 4.

3.1 HYDRAULIC BEHAVIOR ANALYSIS

Pressures and flows in the system exhibited contrasting behavior in response to changes in the DP. Figure 3.2 shows how pressures and flows changed over time in the conservation (S1) or load-shifting (S2) scenario compared to the base. Each line represents the distribution of changes (Δ) across the network at a time step. The thick, blue line segment signifies the range in which 95% of node or link values fall at that specific time. The thinner, gray segments show the tails of the distribution at that time, or the outer 5% of values.



(a) S1

(b) S1

(c) S2

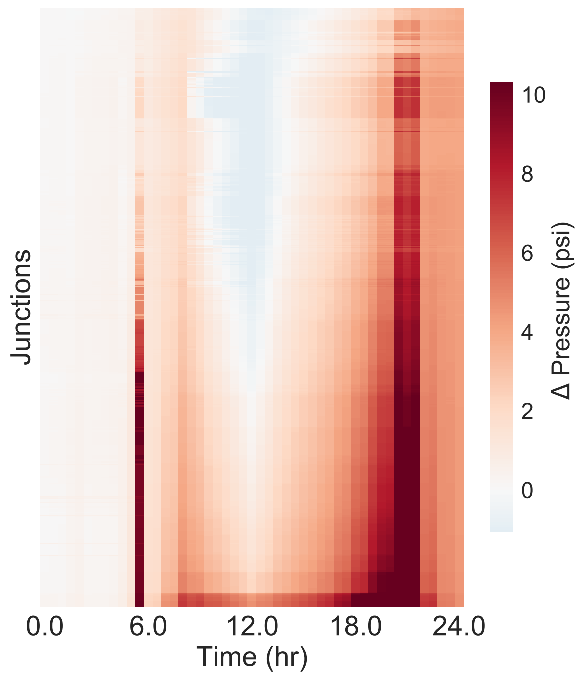
(d) S2

Figure 3.2: Distribution of changes (Δ) in pressure and flow across the network for each time step under conservation (S1) and load-shifting (S2) scenarios compared to the base.

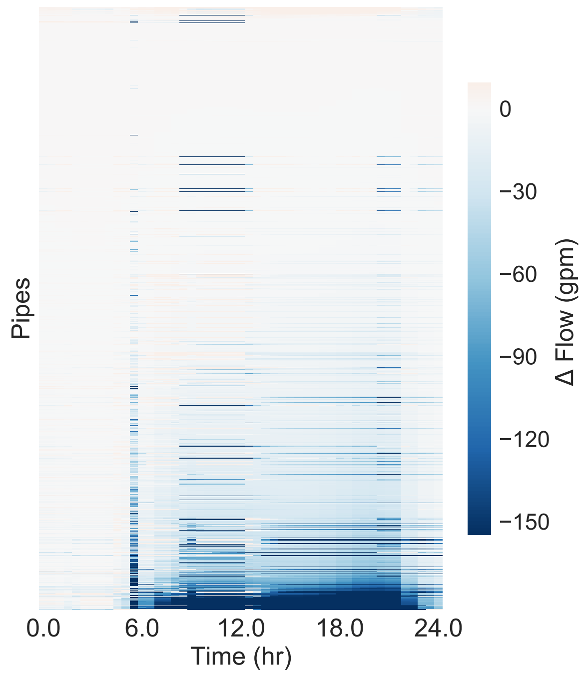
Overall, water pressures in S1 increased across all times from S0, while flows decreased. The greatest positive changes in pressure, as well as the most extreme differences in flow, occurred around high usage times for S1, as seen in Figure 3.2a and 3.2b. Despite differences in pressure and flow behavior, both experienced significant changes during the second demand peak at 21 hours, as evidenced by the increased variances and Δ peakiness at that time. In general, Net 4 Δpressure had a larger variance across the network at each time, however there were more extreme Δflow values, or longer tails. Peak demands in the S0 and S1 profiles appear simultaneously and the difference in consumption was the greatest at these times.

Figures 3.2c and 3.2d show that pressures and flows in S2 alternated between increasing and decreasing from S0, more so than in S1. These swings coincided with differences in the DPs of the two scenarios. For example, there is more variability, as well as a negative change in pressure at night during hours of traditionally low consumption because demands at these times in S2 are much higher due to the load-shifting. Similarly, difference in demands between S2 and S0 are small during the traditional morning peak, thus there is less variability in Δ pressure and flow. This suggests that times where there were larger differences between the DPs of two scenarios had a greater influence on metric values.

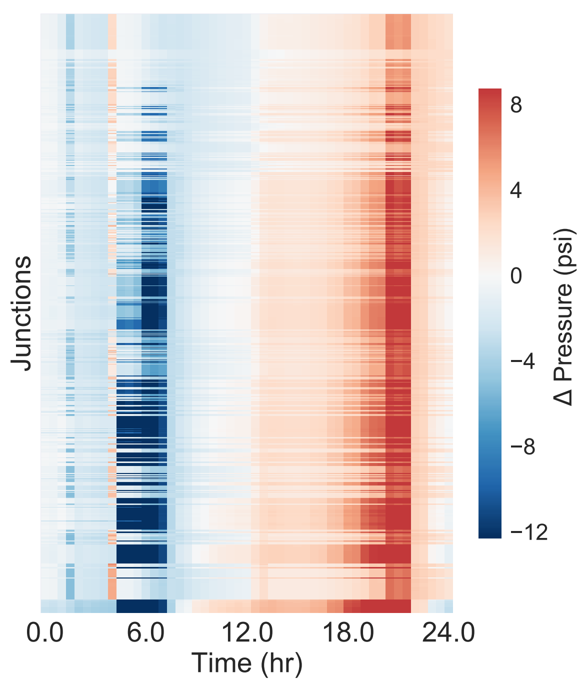
Figure 3.3 illustrates more detailed behavior of pressures and flows in Net 4, and verify the results. The heat matrices show all pressure and flow change (Δ) distributions in the network over 24 hours. Each colored row in the matrix represents the distribution of values for a single feature, e.g. junction or pipe. The features of the network were ordered by median values. In this figure, blue represents a decrease in value from S0 and red constitutes an increase. As the color gets darker, the magnitude of change is greater, and neutral-colored cells suggest little to no change from S0. Figure 3.3b has a large majority of neutral-colored cells, which suggests that changes in flows were driven by a minority number of pipes during high usage times. Meanwhile, the coloring of Figure 3.3a indicates changes in water pressures were more spread out across the network and time. In Figure 3.3c, the contrast between the morning and afternoon shows that Δpressures in the majority of the junctions react similarly when demands in S2 are noticeably greater in the morning versus when the afternoon peaks in S0 eclipses the DP of S2. Most pipes or junctions follow behavior seen in the previous plots of Figure 3.2, as expected. In S1, there were no changes at night when usage was minimal and users were typically inactive, however the figures show increased activity in S2 overnight due to load-shifting.



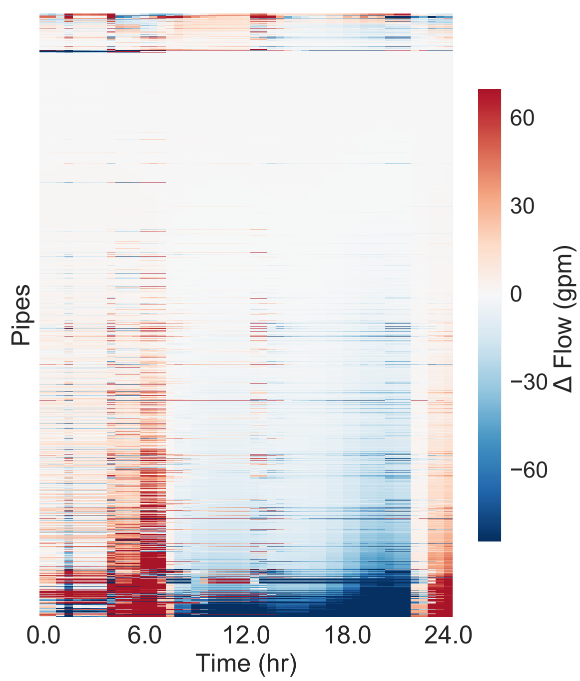
(a) S1, Water Pressure



(b) S1, Flow Rate



(c) S2, Water Pressure



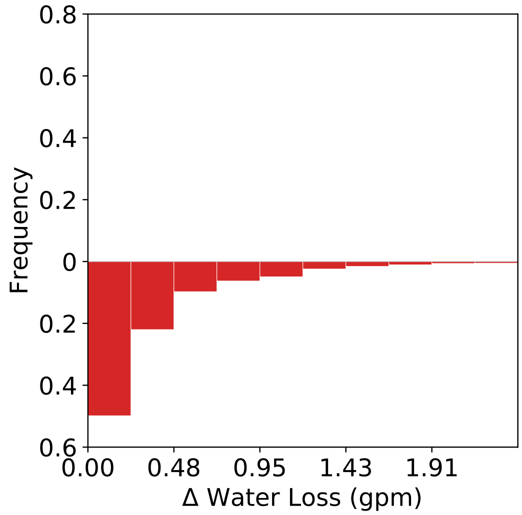
(d) S2, Flow Rate

Figure 3.3: Heat matrices of all changes (Δ) in pressure and flow distributions in the network over time under conservation (S1) and load-shifting (S2) scenarios compared to the base.

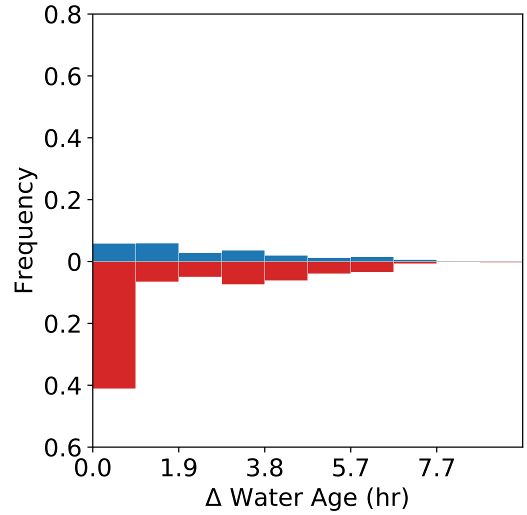
3.2 NETWORK PERFORMANCE

The performance of Net 4 was evaluated using the metrics of water loss, water age, energy loss, and peak flow. The comparative histograms, as seen in Figure 3.4, show changes (Δ) in the four metrics between the conservation (S1) and base (S0) scenarios. For illustration purposes, values in the upper 1% tail of the distribution are not shown. A value decrease from S0 is illustrated by blue bars on the top half of the plot, which indicates an improvement. An increase from S0 is illustrated by the red bars on the bottom half of the figure, indicating a decline in performance. For example, in Figure 3.4b, the red bars (increases) were more perceptible than the blue (decreases), indicating an overall increase in water age, but mostly of values less than 1 hour. The histogram supported the percent-difference in the water age metric from S1 compared to S0, which was 0% from Table 4.2. Table 4.2 contains percent-differences based on the Δ values, as described in detail in Chapter 4.

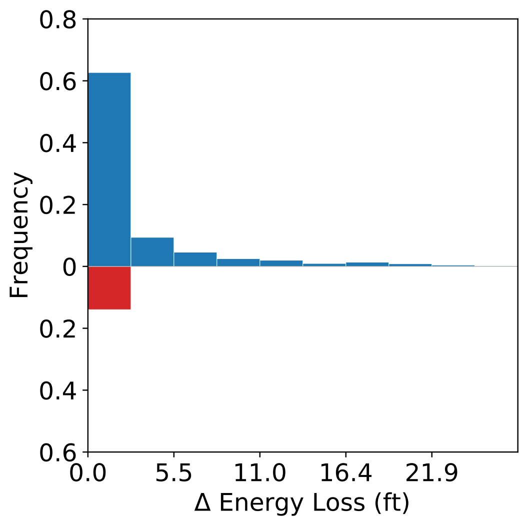
In S1, Net 4 simulations resulted in an overwhelming increase in water loss from the base scenario, or a worsened performance, which corresponded to the overall increase in pressures, seen in Figure 3.2a. The water loss performance in S1 changed by -6.1% from the base, according to Table 4.2 in Chapter 4, which contains percent differences based on Δ values. For most node or pipe features, the differences in energy loss and peak flow from S0, respectively, decreased, which was an improvement in performance. The percent differences between S1 and S0 for energy loss and median peak flow were 36.9% and 24.1%, respectively. These results were expected since energy losses and peak flow rates are dependent on flows, which decreased with water demands. Subsequently, this increased detention times in the network. In Figure 3.5, the comparative histograms of values between the load-shifting (S2) and base (S0) scenarios show similar results. However, the histograms were more equalized between value increases (red) and decreases (blue), which resulted in small changes of -0.5%, 0%, 0.1%, and 27.3% for water loss, median age at 24 hours, energy loss, and median peak flow, respectively.



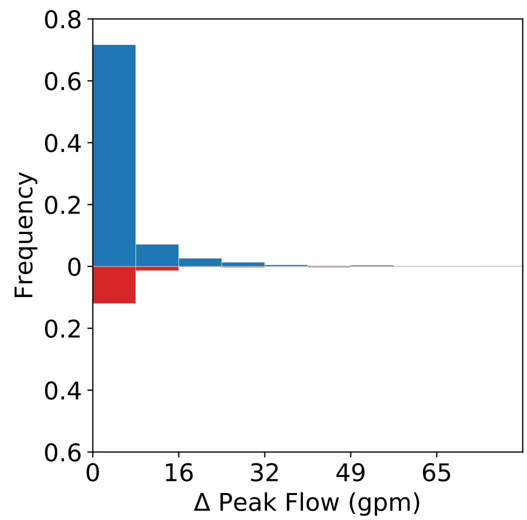
(a) S1, Water Loss



(b) S1, Water Age

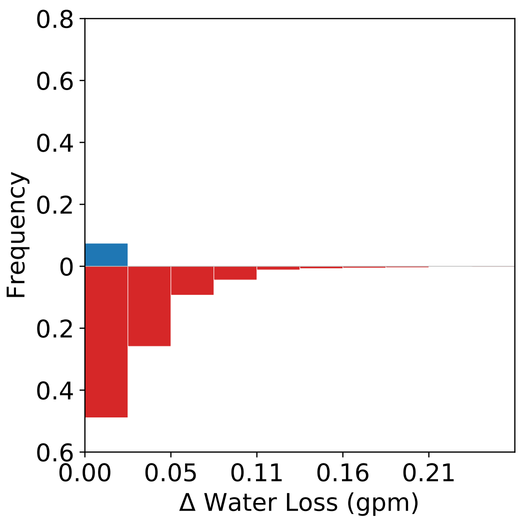


(c) S1, Energy Loss

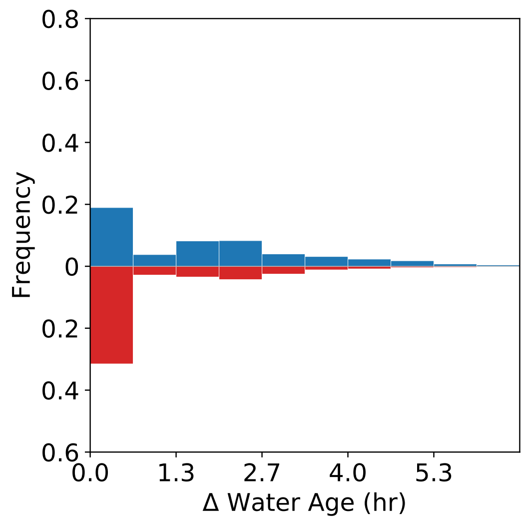


(d) S1, Peak Flow

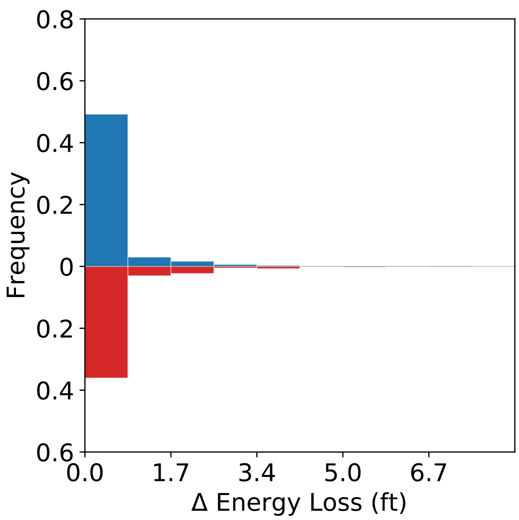
Figure 3.4: Histograms of changes (Δ) under the conservation (S1) scenario from the base for water loss, water age, energy loss, peak flow.



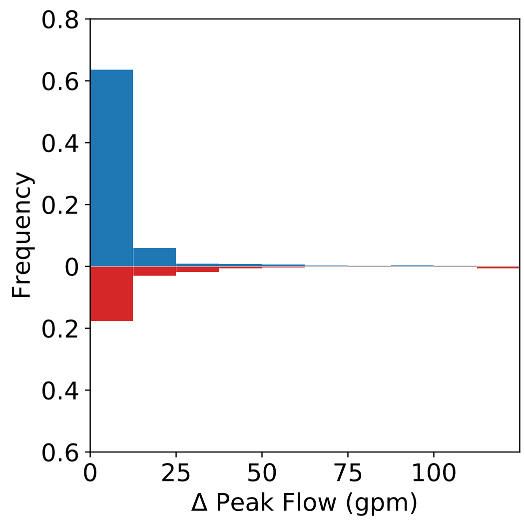
(a) S2, Water Loss



(b) S2, Water Age



(c) S2, Energy Loss



(d) S2, Peak Flow

Figure 3.5: Histograms of changes (Δ) under the load-shifting (S2) scenario from the base for water loss, water age, energy loss, peak flow.

3.3 SCENARIO COMPARISON

The comparison of performance among the demand scenarios, shown in Figure 3.6, was based on resulting metric values (I), which can be found in Table A.1 of Appendix A. Similar to Figure 2.1, the gray, dashed blue, and solid green lines represent results for the base (S0), conservation (S1), and load-shifting (S2) scenarios. For each metric, the results from the three scenarios were normalized such that 1 represents the best performance (smallest value), while 0 is the worst (largest value). Therefore, in Figure 3.6, Net 4 under S0 had the best performance of the three scenarios for water loss and median age metrics, with values of 0.20 MGD and 20.1 hr, respectively. However, S0 had the worst performance for energy loss and median peak flow, $208 \times 10^3 ft$ and 27.3 gpm, respectively. By contrast, S1 performed the worst in terms of water loss and median age, 0.21 MGD and 24.0 hr, respectively, and the best for energy loss, $131 \times 10^3 ft$, and median peak flow, 20.5 gpm. Net 4's performance under S2 fell somewhere between the results of the other demand scenarios, with values of 0.20 MGD, 21.3 hr, $207 \times 10^3 ft$, and 22.5 gpm for water loss, median age, energy, and median peak flow respectively. However, S2 performed better than at least one other scenario for three out of four metrics. Analysis of additional UWNs showed similar behavior to the benchmark, which is discussed in Chapter 4 and seen in Figure 4.1.

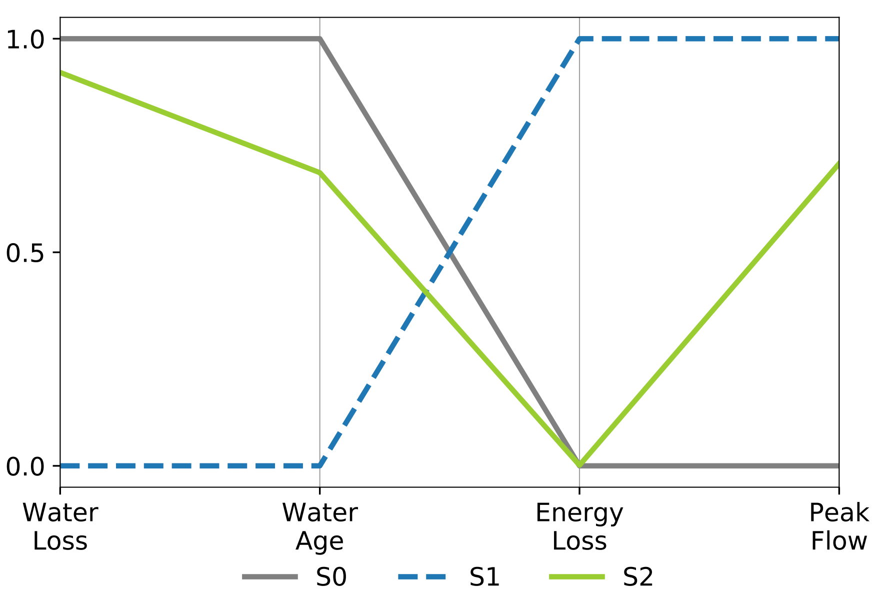


Figure 3.6: Comparison of benchmark network (Net 4) performance metrics I_w, I_a, I_e, and I_f among scenarios base (S0), conservation (S1), and load-shifting (S2).

Chapter 4: Global Analysis

The analysis for this study was run on 6 additional real-world networks from Jolly et al. (2014). Individual figures for these UWNs, such as those seen in Chapter 3, are provided in Appendix A. Network properties for the benchmark and evaluated UWNs are shown in Table 4.1. From a survey of these properties, the total pipe lengths spanned $300 - 850 \times 10^3$ ft, and the daily demands ranged from $1.5 - 2.5$ MGD.

Table 4.1: Network Properties

	Pipe Length *(K-ft)*	Base Demand *(MGD)*	No. Nodes	No. Pipes
Net 3	300	2.0	275	366
Net 5	317	2.3	427	496
Net 6	404	1.6	548	644
Net 7	450	1.5	485	603
Net 1	547	1.5	798	907
Net 8	811	2.5	1332	1614
Net 4	854	1.5	964	1156

The results for water loss, age, energy, and flow of all networks from simulations of the conservation and load-shifting scenarios are listed in Table 4.2 as percent-differences from the base, based on Δ. The percentages are shown as $-\Delta$ for illustrative purposes so that the signs make more intuitive sense in terms of decline (–) and improvement (+) in performance. Since this study was interested in potential savings, a positive percentage indicated a decrease from the S0 value, or an improvement, while a negative meant an increase, or declined performance. By contrast, Table A.1 in Appendix A provides the actual performance metric values for the entire network under each scenario, instead of differences. The UWNs in Tables 4.1-4.2, A.1, and Figure 4.2 were ordered by ascending pipe length.

For each UWN evaluated, the resulting metric values (I) for network performance under the three scenarios were compared, as shown in Figure 4.1, which was generated from values in Table A.1 in Appendix A. The base (S0), conservation (S1) , and load-shifting (S2) scenarios are represented by the solid gray, dashed blue, and green lines, respectively. Results for the four performance metrics were normalized

Table 4.2: Performance Metric Results in Percent Differences (-ΔI)

	Conservation (S1)					Load-Shifting (S2)				
	D *(MGD)*	-ΔI_w %	-ΔI_a %	-ΔI_e %	-ΔI_f %	D *(MGD)*	-ΔI_w %	-ΔI_a %	-ΔI_e %	-ΔI_f %
Net 3	2.0	-9.9	-6.3	2.0	14.1	1.0	2.4	0.0	6.4	17.9
Net 5	2.3	-2.8	-97.7	11.4	28.5	1.1	-2.1	-58.6	1.7	30.8
Net 6	1.6	5.3	-88.0	61.9	0.6	0.8	2.7	-0.9	6.7	39.7
Net 7	1.5	-11.9	-2.2	15.9	12.3	0.8	1.7	0.0	4.8	32.2
Net 1	1.5	-3.8	-4.7	18.6	50.0	0.8	0.9	0.0	1.0	41.2
Net 8	2.5	-5.6	-14.6	35.1	14.6	1.2	2.1	0.0	5.1	28.8
Net 4	1.5	-6.1	0.0	36.9	24.1	0.8	-0.5	0.0	0.1	27.3

such that the smallest value is shown at 0 and the largest is drawn at 1. For example, in Figure 4.1f, the DP for S2 resulted in the smallest values for I_w and I_a, or best performance, amongst the three demand scenarios, so the solid green line is drawn at one. In the same figure, S1 had the highest values for metrics I_w and I_a, resulting in the worse performance and the dashed blue line is drawn at zero. The UWNs all perform similarly under the three scenarios. For all networks, both emerging demand scenarios improved from the base in energy loss and peak flow. S1 frequently results in the worst performance for water loss and age, but leads amongst the three scenarios for energy loss and peak flow metrics. By contrast, in S2, networks generally perform well in terms of water loss, water age, and peak flow compared to the other scenarios.

The plots in Figure 4.1 indicate that there is some trade-off for each demand scenario. Interestingly, in Net 3, the load-shifting scenario does well across the board. UWNs under S1 saw a greater improvement in energy loss than S2. Variations in performance behavior could be attributed to differences in network configurations, elevation, topology, consumer aggregation, and other characteristics. Utilities could benefit from investigating what shape of DP would optimize performance to inform and customize their approach to demand management.

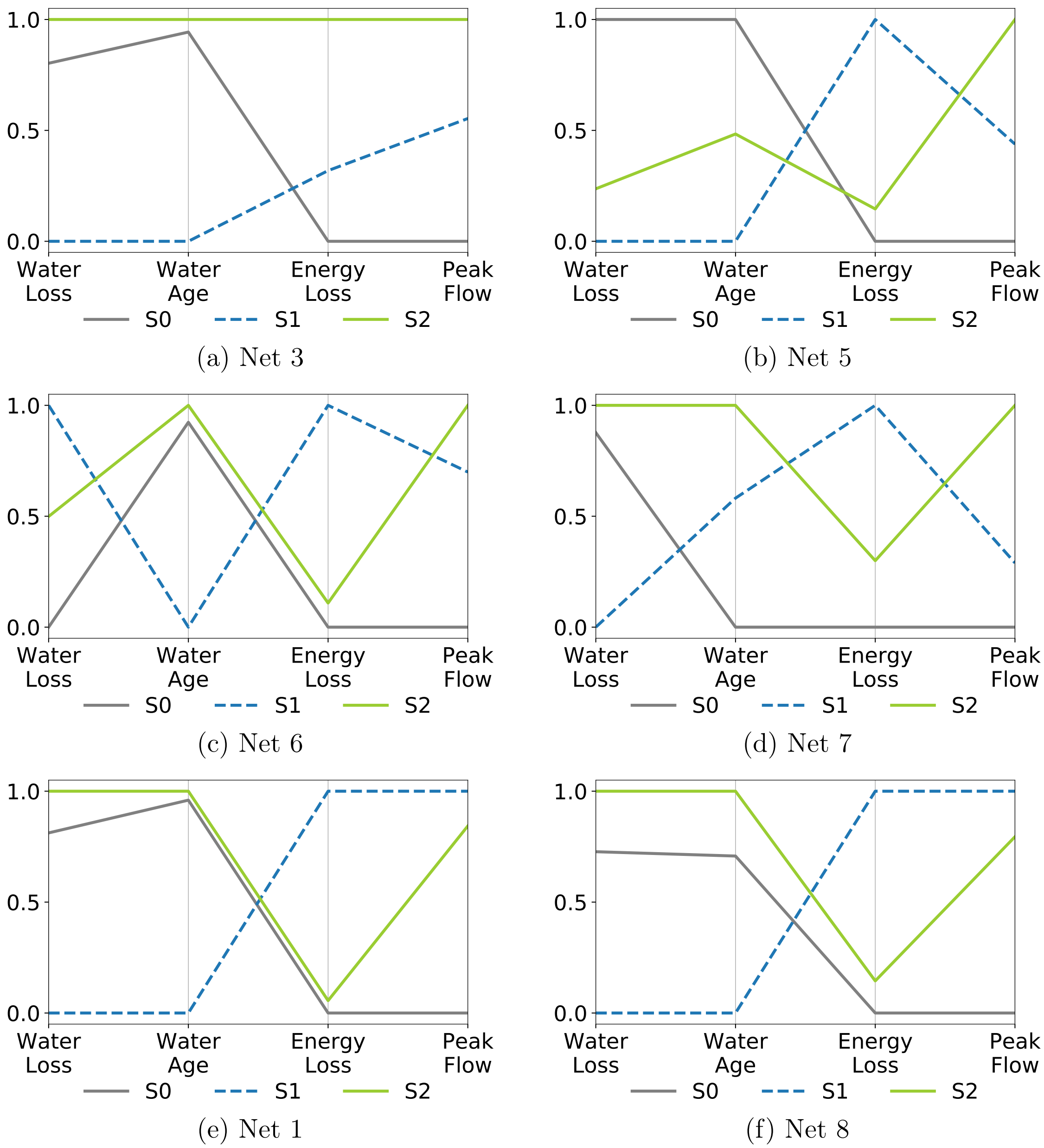
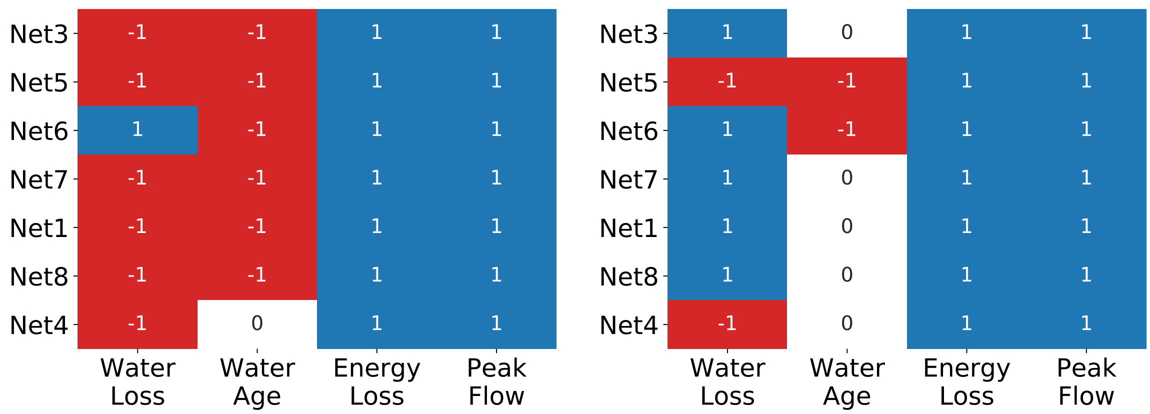


Figure 4.1: Comparison of network performance metrics I_w, I_a, I_e, and I_f, among scenarios base (S0), conservation (S1), and load-shifting (S2).

Figure 4.2 compares the results for all UWNs and percent-difference (-Δ%) values under the emerging and base scenarios. The blue-colored cells (1) demonstrated an improvement in the emerging scenario (S1 or S2) compared to the base (S0), while the red cells (-1) indicated a decline in performance. Table 4.2 gives the underlying percent-difference values.



(a) S1 (b) S2

Figure 4.2: Changes (-Δ%) in network performance under conservation (S1) and load-shifting (S2) scenarios compared to the base.

Network performance based on energy loss and peak flow improved for all networks under both S1 and S2. In the conservation scenario, the improvement was expected because demands were reduced, and consequently, flows decreased. Energy losses were also dependent on flows, and there was a significant improvement in I_e under S1. However, the flow reduction in S1 increased travel times across the network, thus degrading water quality, as represented by the column of mostly red (-1) cells in Figure 4.2a. The performance metric for water loss also worsened for the majority of UWNs, which corresponded with the increases in pressures similar to those seen in Figure 3.2a. In contrast, performance under the water loss metric improved slightly in S2, as seen in 4.2b and Table 4.2. There was little to no change in the water age metric under S2.

The results suggested definite savings potential for energy in either emerging demand scenario, and the possibility of minimizing infrastructure upgrades due to lower peak flows. However, a drawback of the water conservation scenario was the increased public health risk as a consequence of degraded water age. Declined performance with regards to the water loss metric necessitates more stringent control programs on the utility-side. Reduced demands with increased water losses create a financial burden, due to revenue loss and rising maintenance costs, if these effects are unaccounted for in water operations and planning.

Chapter 5: Discussion

The goal of this study was to evaluate network performance under various demand scenarios, with an interest in determining savings for utilities as DM becomes more extensive. The performance results showed savings potential, but given the steep reduction in demand, savings were not as great as expected. Water loss increased under the conservation scenario corresponding with greater pressures, which could have been adversely affected by the demand-driven modeling and lower flows. The load-shifting scenario experienced only a slight improvement in water loss, therefore, utilities would not benefit from water savings under these emerging DPs. The water losses may end up costing utilities due to associated energy and maintenance requirements.

Network performance based on energy and flow metrics improved in both emerging scenarios due to reduced demand, which suggests potential cost savings in energy use and infrastructure. The savings potential could increase if the cost of energy were considered because electricity rates are greater during peak demand. However, these savings may be at the expense of water quality, since some UWNs experienced significant increases in water age, particularly during the conservation scenario.

Some variance in results could be attributed to the differing network topologies and characteristics that may have underlying effects on values calculated. Exact savings could not be quantified due to factors that are unobservable in the networks and simulations, such as measurement accuracy, energy and water rates, efficiency of the infrastructure, maintenance needs, detailed user and demand attributes, etc. However, the results revealed insights into network performance under emerging demand profiles.

The results highlighted the implications on water management and planning from the network infrastructure and utility side. Water service providers need to adapt to changing usage behaviors in order to capitalize on energy savings while maintaining water quality since it is not feasible to overhaul existing network design. To adapt, utilities need to adjust network operation, for example, via pumping, valve, and tank storage rules to optimize system performance and maximize savings. Thus, investing in efficient appliances and alternative water sources can be worthwhile to both consumers and providers to dampen and reduce demand diurnals, but would require operational changes in order to realize full benefits. In this study, operational rules remained unmodified through all simulations.

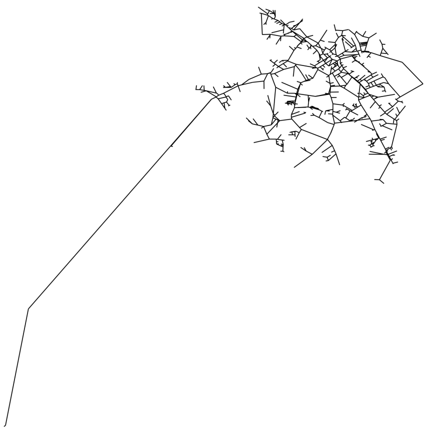
Further investigation is warranted to address limitations, implement model improvements, and expand the scope of the analysis. While EPANET2 was suitable for the extent of this study, there are limitations to using a demand-driven model. Since demands are also a function of pressure, future iterations of this work could shift to pressure-driven analysis. The model may be improved by extending the simulation period beyond 24 hours to evaluate performance on a multi-day or weekly basis. Formulation used for energy estimates may be expanded to include pumping information and the cost of energy. To expand the analysis, additional demand scenarios using DPs derived from smart-metered data may be considered. Other considerations are the changes in demands due to rapid urban growth as well as depopulation in some cities. Since residential consumers are relatively similar, predictable, and homogeneous in behavior, this study assumed only residential demand in the UWN. Incorporating industrial and commercial users, along with their corresponding DPs, would be worthwhile to better understand the effects of demand management on network performance. It would also be interesting to see similar work done as a case study on a larger real-world hydraulic model where more detailed user and demand information is available.

Appendix A: Additional Results

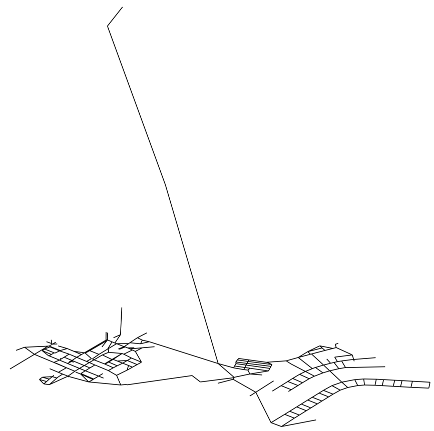
Results and figures from simulations of additional networks in Chapter 4 are provided in this appendix.

Table A.1: Performance Metric (I) Summary

	Base (S0)				Conservation (S1)				Load-Shifting (S2)			
	I_w *(MGD)*	I_a *(hr)*	I_e *(k-ft)*	I_f *(gpm)*	I_w *(MGD)*	I_a *(hr)*	I_e *(k-ft)*	I_f *(gpm)*	I_w *(MGD)*	I_a *(hr)*	I_e *(k-ft)*	I_f *(gpm)*
Net 3	0.059	5.3	414.5	57.8	0.065	6.6	406.0	50.7	0.058	5.2	387.9	45.0
Net 5	0.057	8.3	785.3	48.9	0.059	17.8	695.9	42.8	0.058	13.2	772.2	34.9
Net 6	0.166	12.7	411.2	27.2	0.157	24.0	156.6	21.1	0.161	11.8	383.5	18.4
Net 7	0.117	17.2	131.9	27.0	0.131	16.7	110.9	24.8	0.115	16.3	125.6	19.2
Net 1	0.175	12.8	940.4	9.1	0.182	16.2	765.7	5.2	0.174	12.7	930.7	5.8
Net 8	0.182	20.1	188.2	23.4	0.192	23.8	122.0	18.6	0.178	18.6	178.6	19.6
Net 4	0.200	20.1	207.7	27.3	0.212	24.0	131.1	20.5	0.201	21.3	207.6	22.5

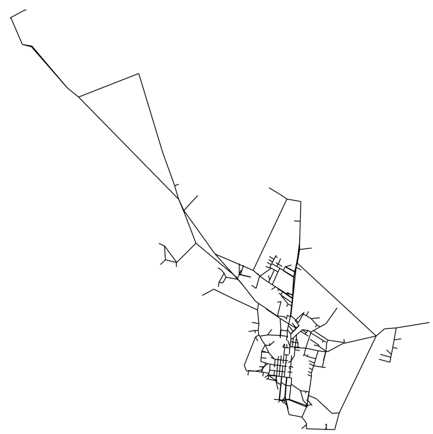


(a) Net 1

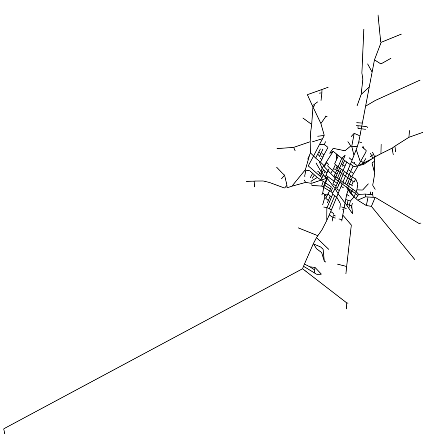


(b) Net 3

(c) Net 5



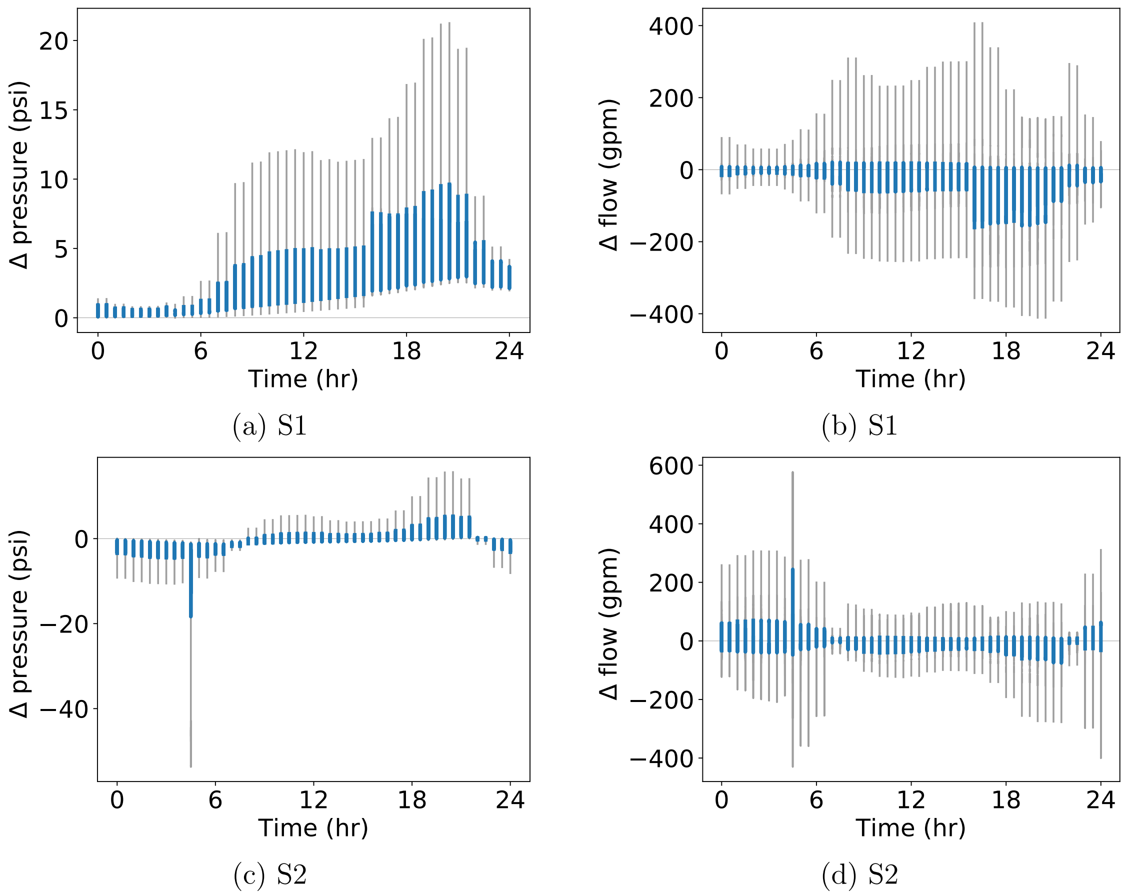
(d) Net 6



(e) Net 7

(f) Net 8

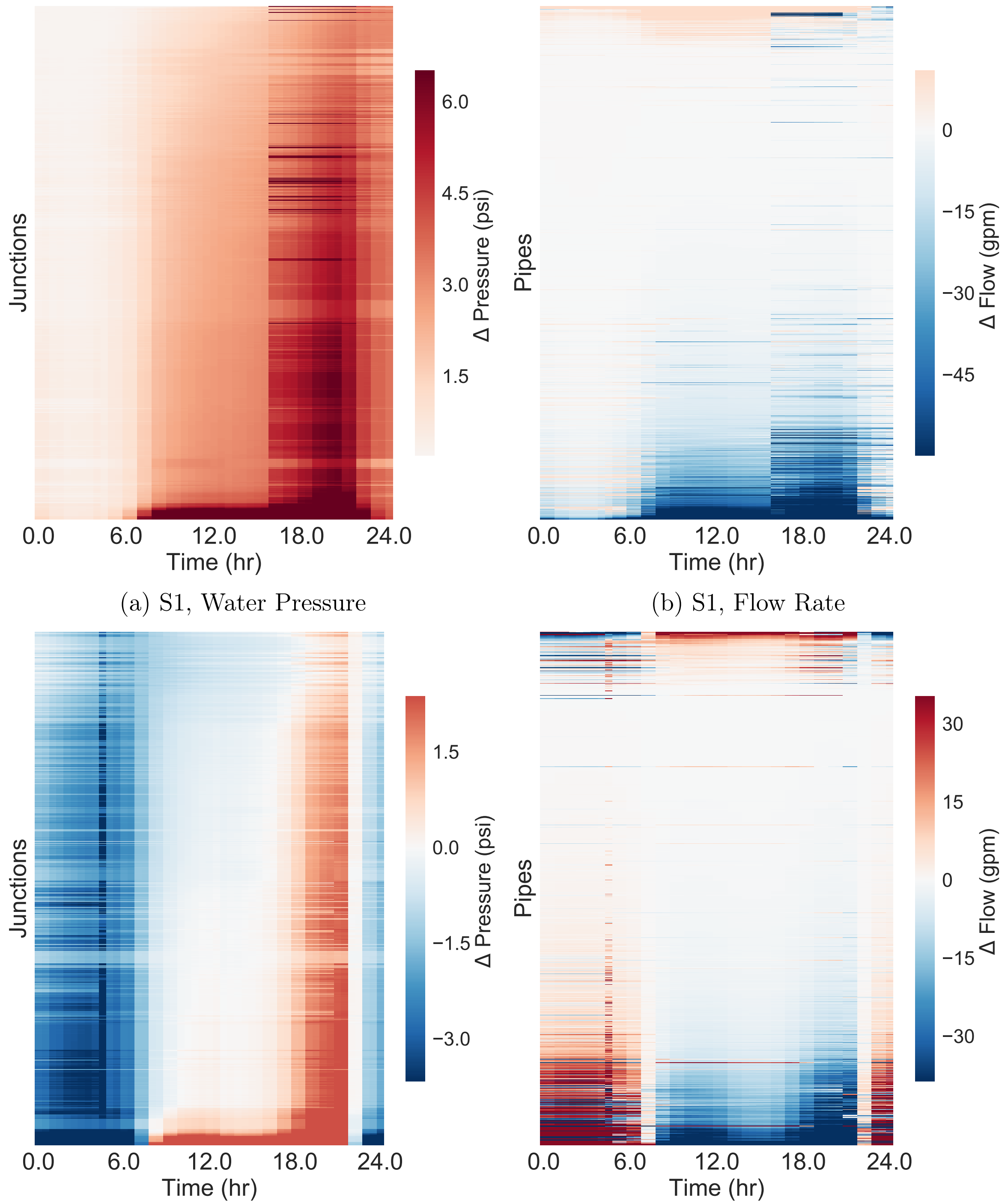
Figure A.1: Topology of networks.



(a) S1 (b) S1

(c) S2 (d) S2

Figure A.2: Distribution of Δ pressure and flow across the Net 1 for each time step under S1 and S2.



(a) S1, Water Pressure

(b) S1, Flow Rate

(c) S2, Water Pressure

(d) S2, Flow Rate

Figure A.3: Heat matrices of all Δ pressure and flow distributions in the Net 1 over time under S1 and S2.

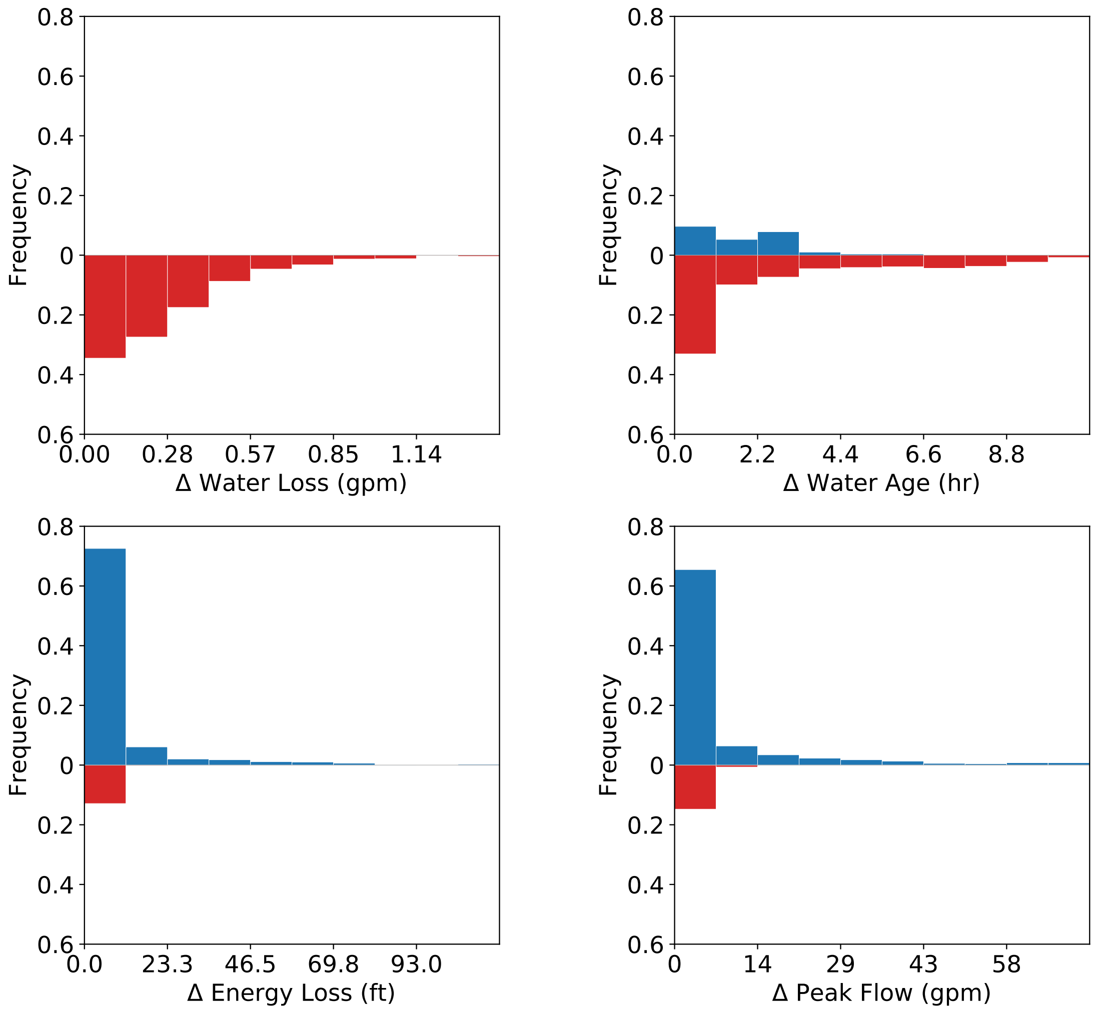


Figure A.4: Histograms of changes in performance metrics for Net 1 under S1.

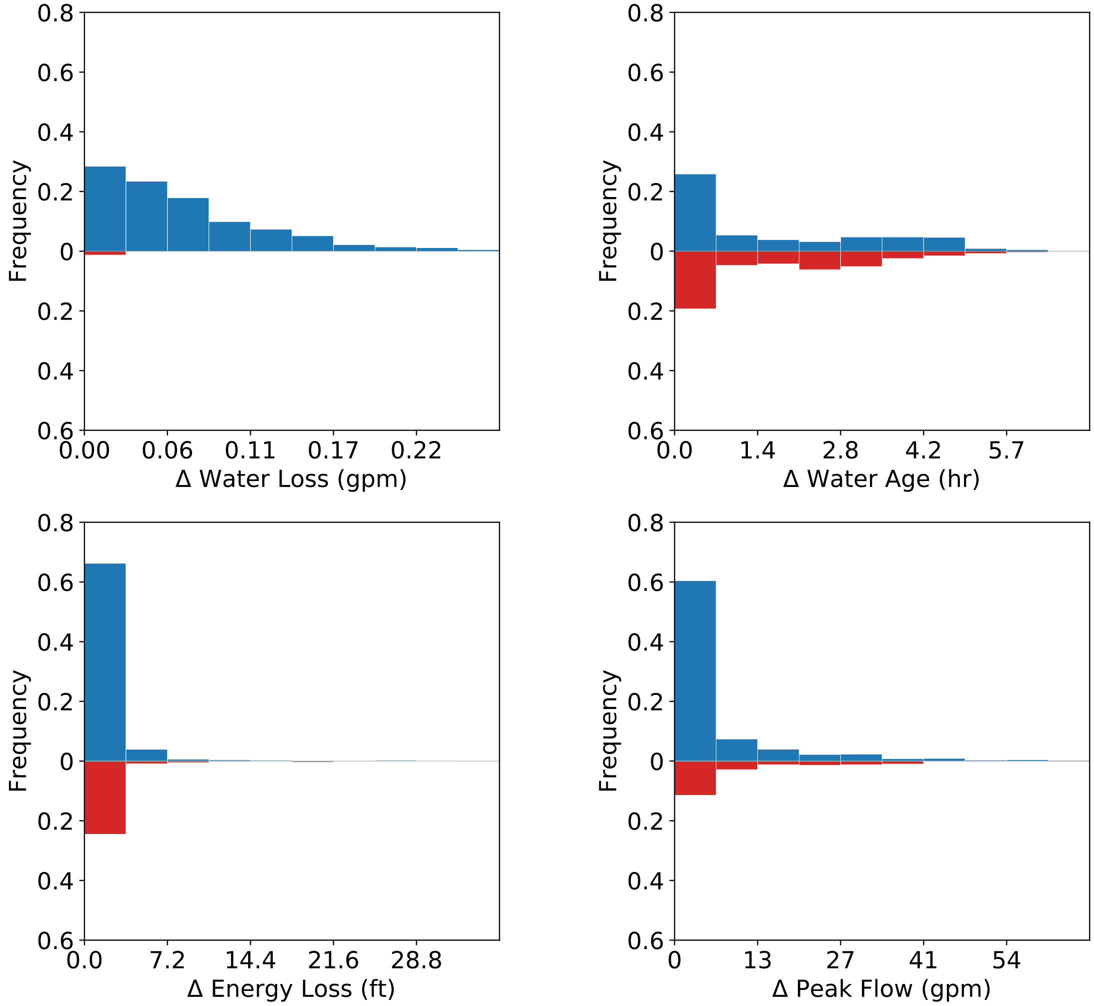


Figure A.5: Histograms of changes in performance metrics for Net 1 under S2.

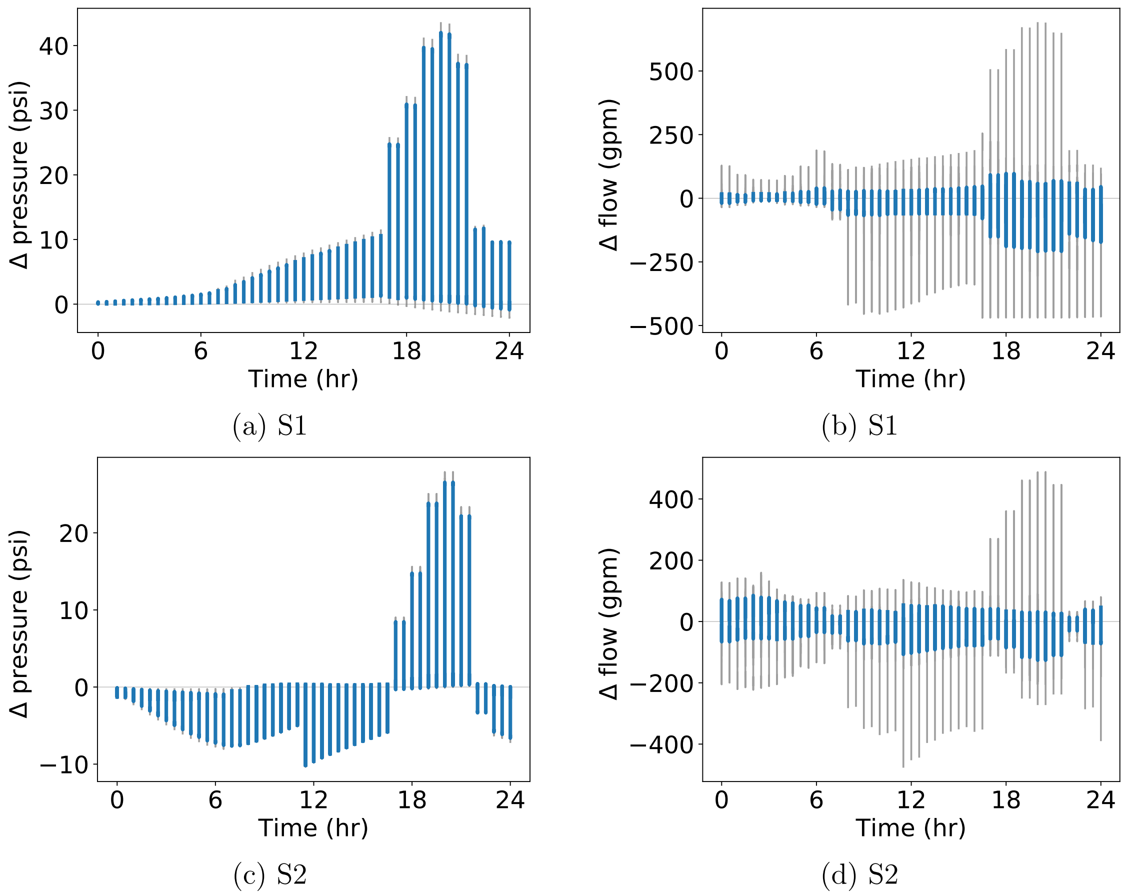


Figure A.6: Distribution of Δ pressure and flow across the Net 3 for each time step under S1 and S2.

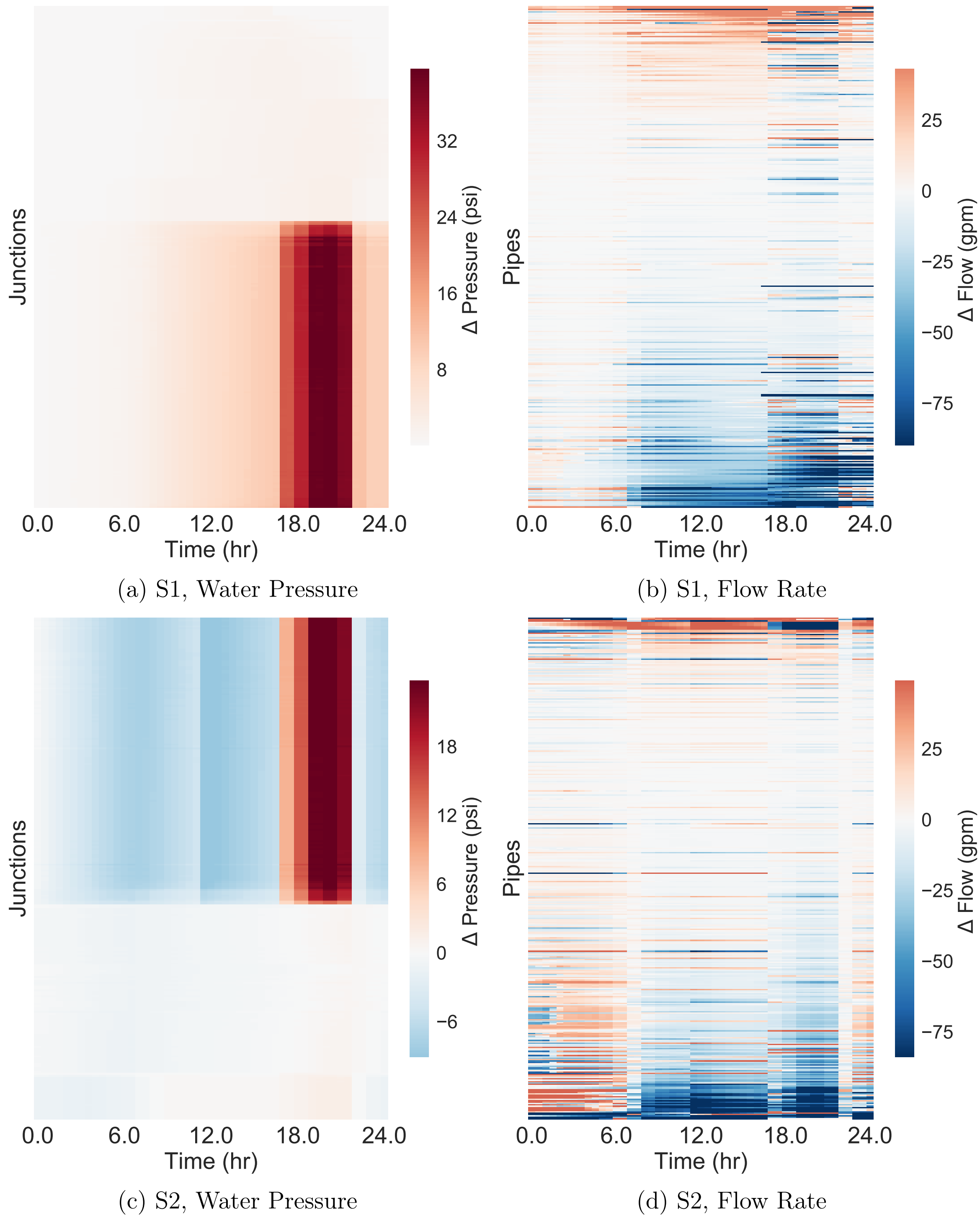


Figure A.7: Heat matrices of all Δ pressure and flow distributions in the Net 3 over time under S1 and S2.

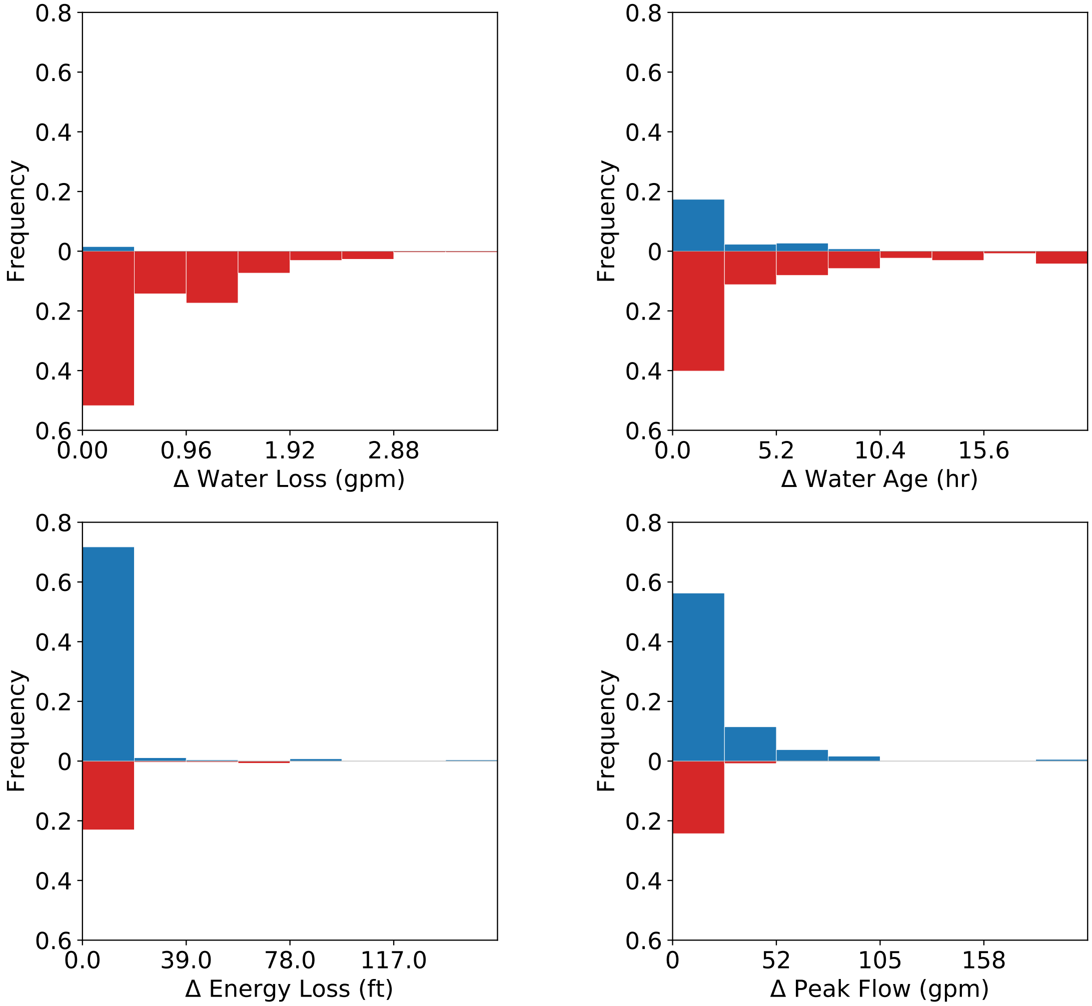


Figure A.8: Histograms of changes in performance metrics for Net 3 under S1.

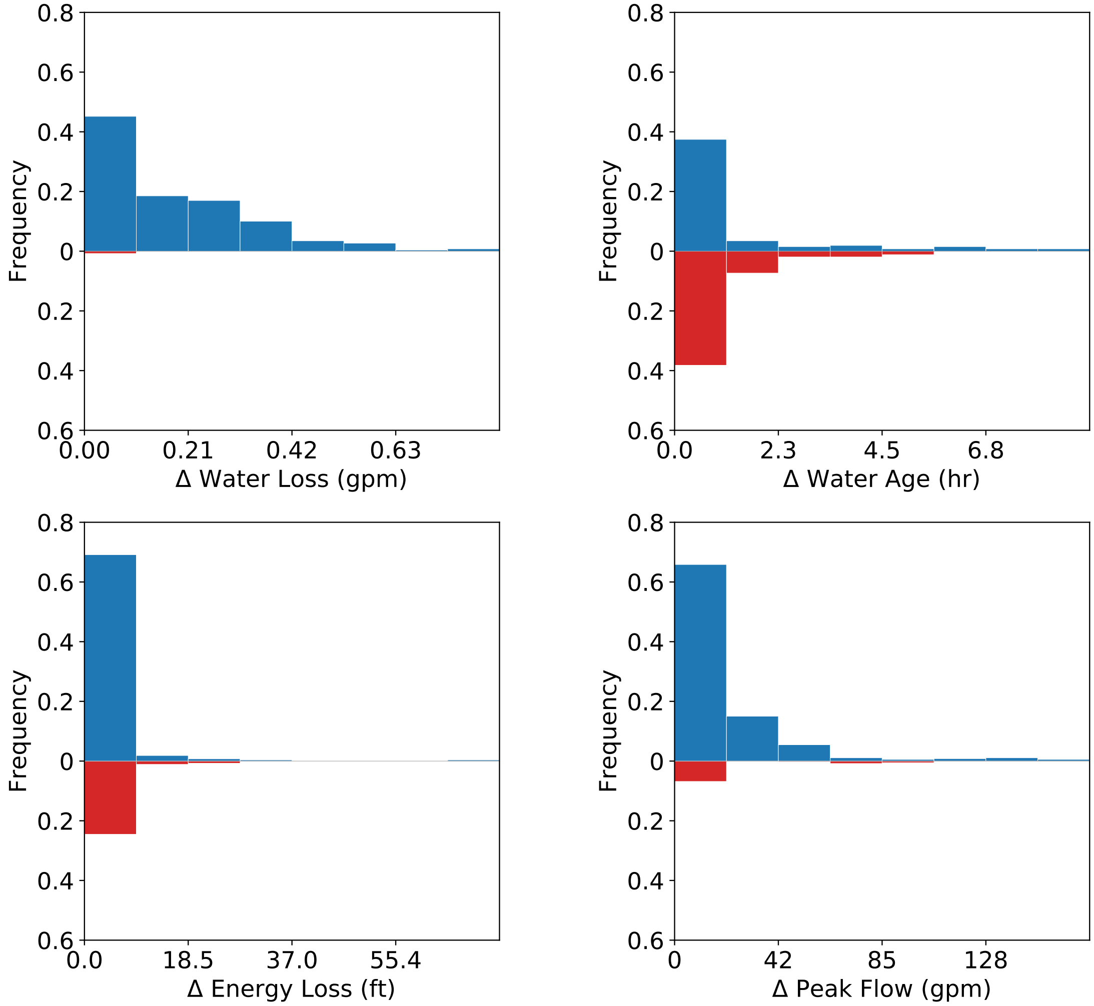
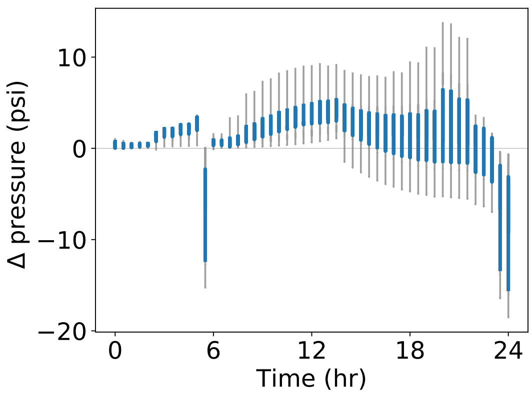
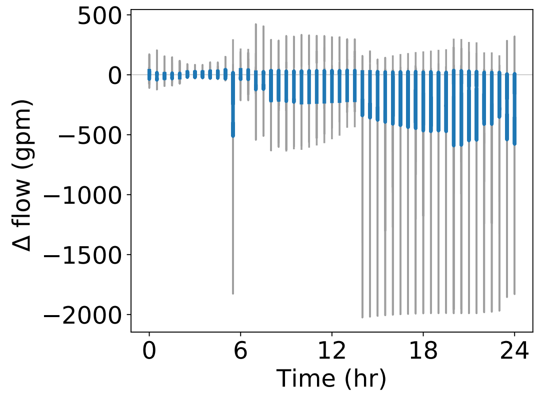


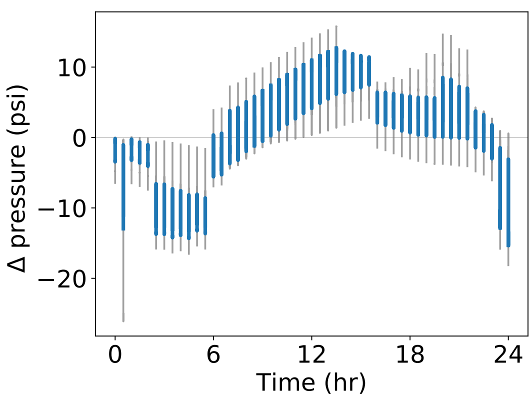
Figure A.9: Histograms of changes in performance metrics for Net 3 under S2.



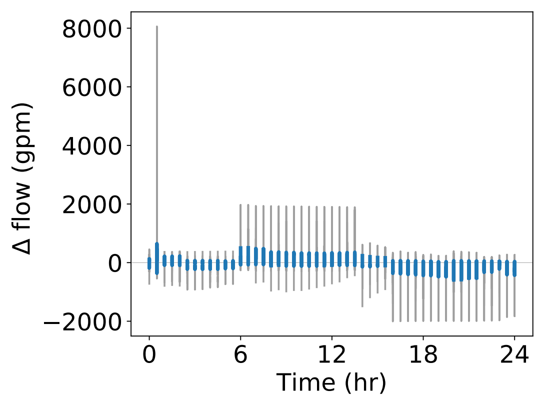
(a) S1



(b) S1

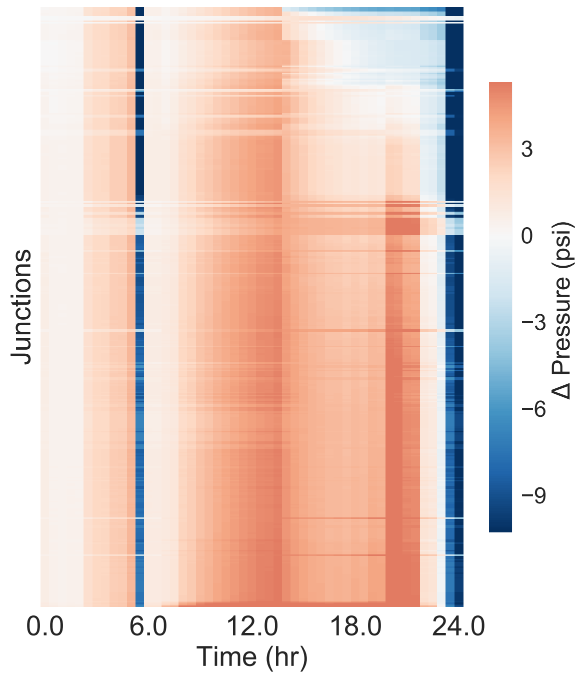


(c) S2

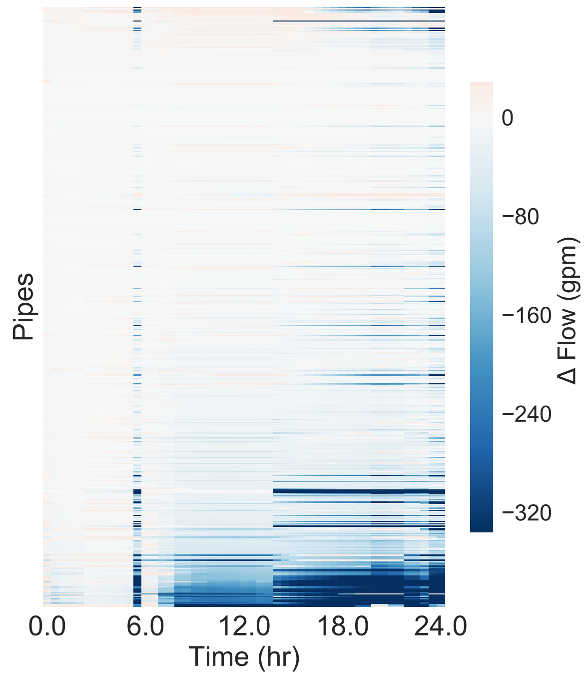


(d) S2

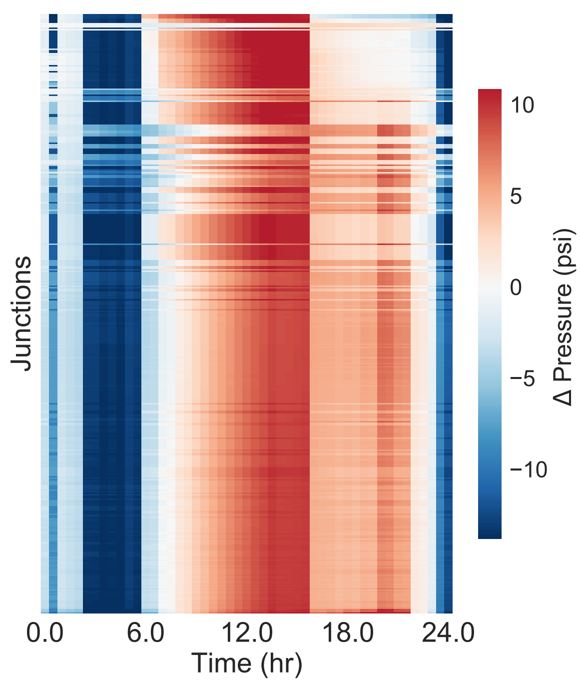
Figure A.10: Distribution of Δ pressure and flow across the Net 5 for each time step under S1 and S2.



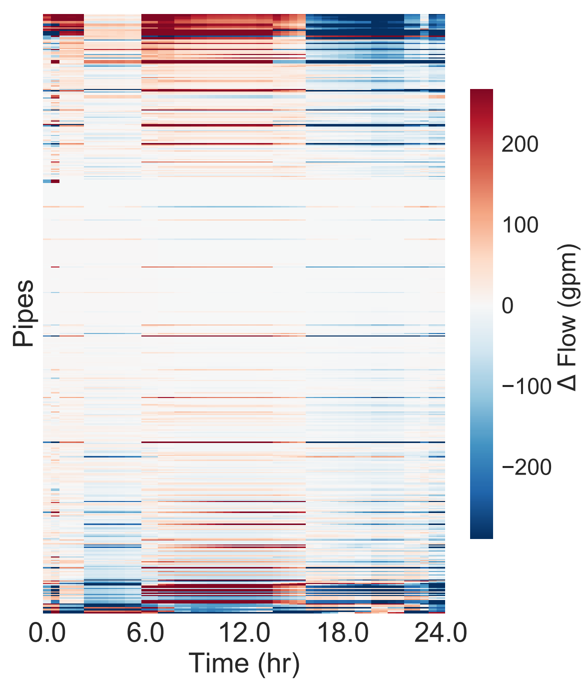
(a) S1, Water Pressure



(b) S1, Flow Rate



(c) S2, Water Pressure



(d) S2, Flow Rate

Figure A.11: Heat matrices of all Δ pressure and flow distributions in the Net 5 over time under S1 and S2.

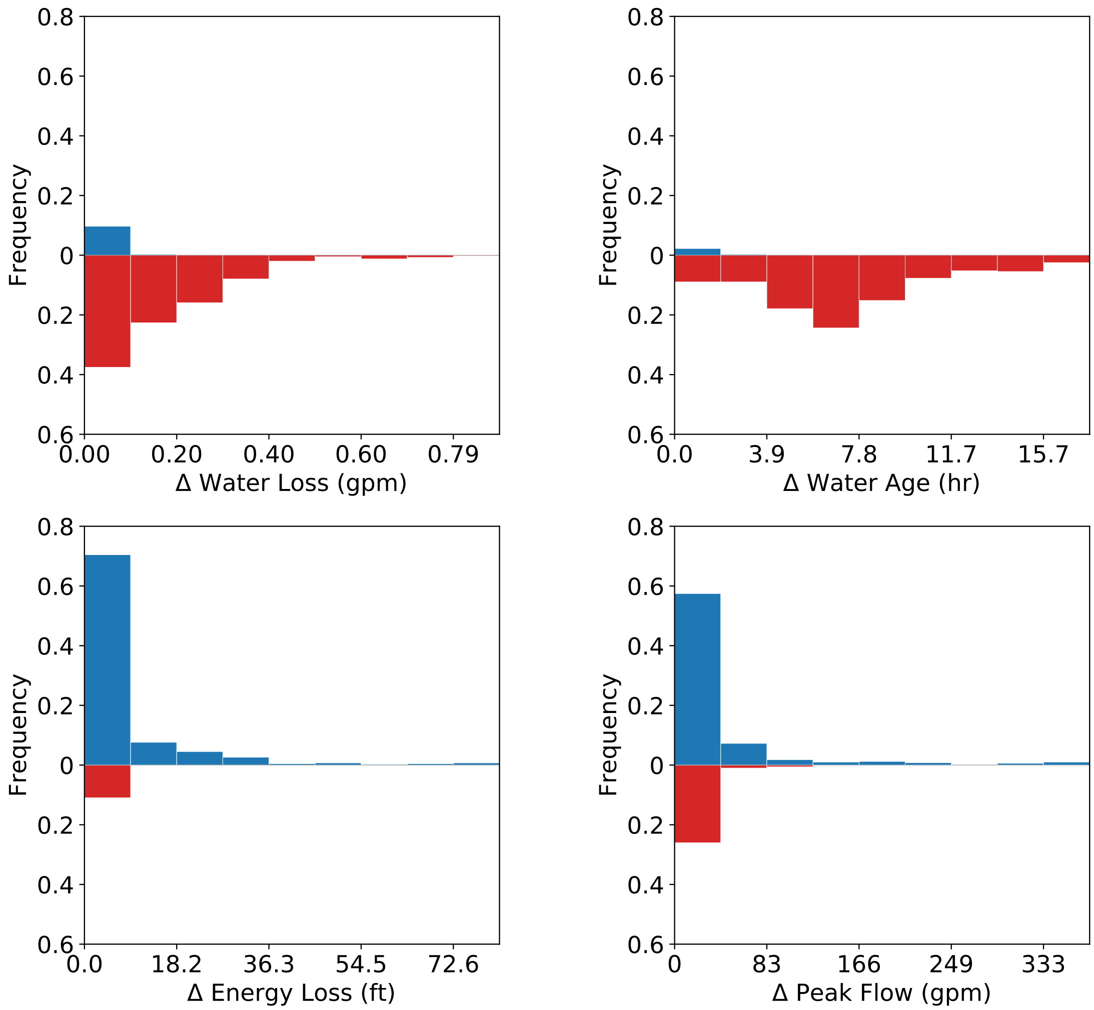


Figure A.12: Histograms of changes in performance metrics for Net 5 under S1.

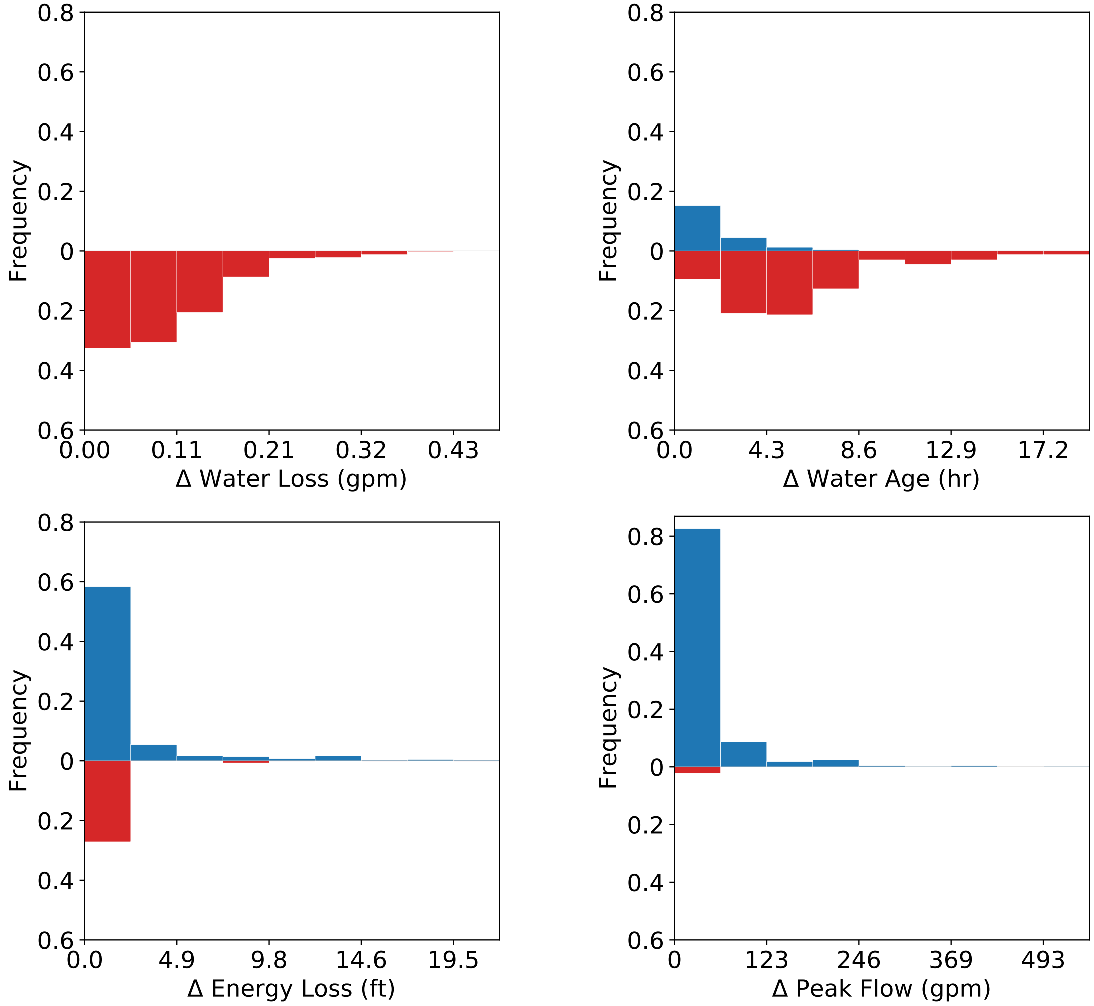


Figure A.13: Histograms of changes in performance metrics for Net 5 under S2.

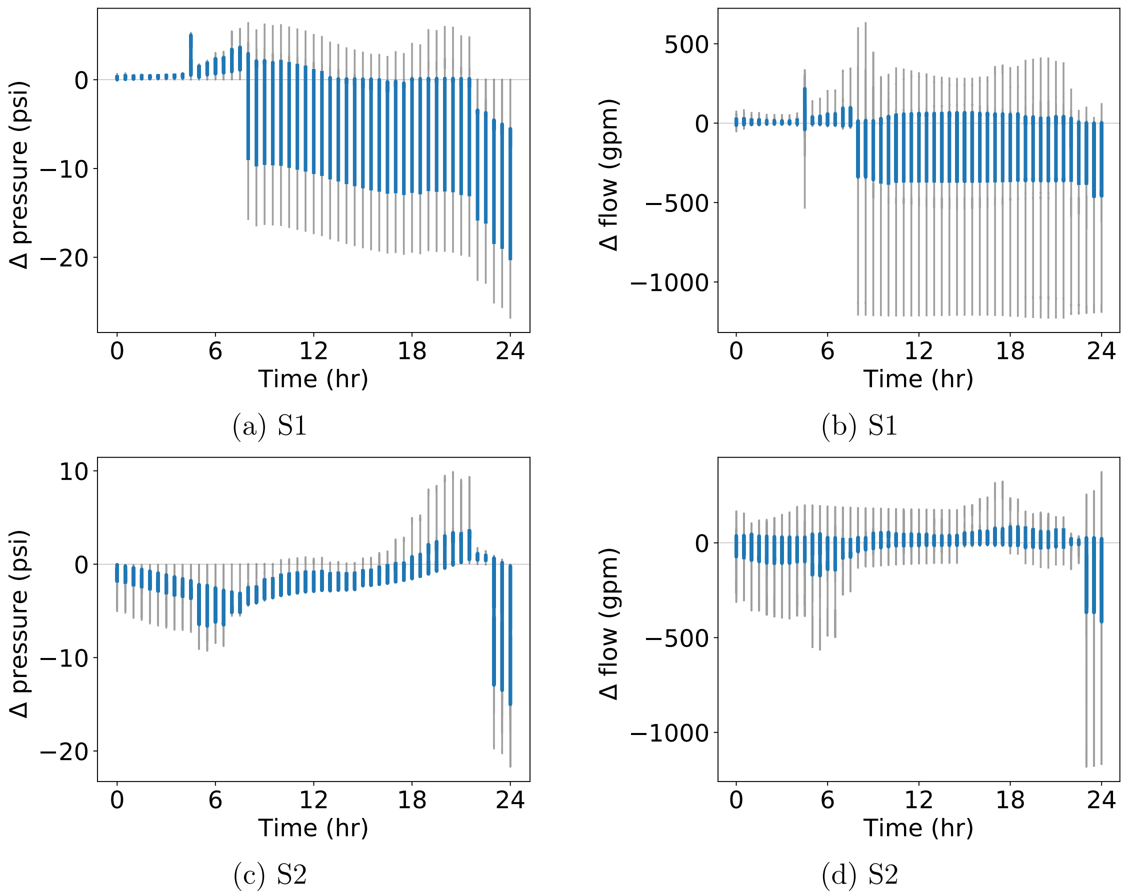
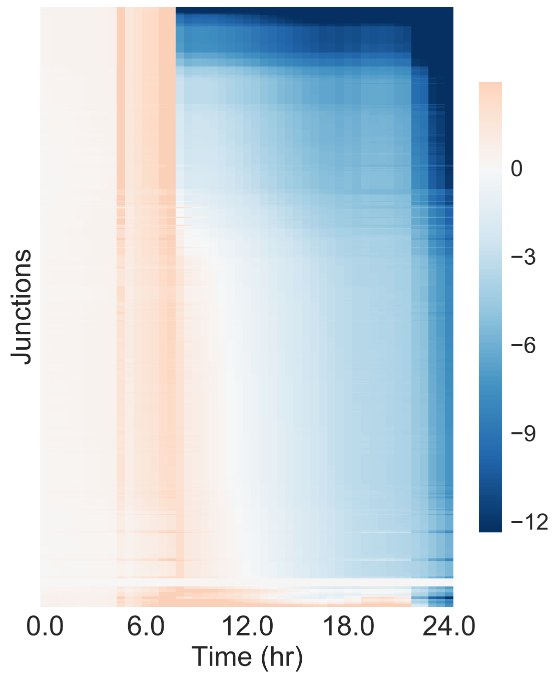
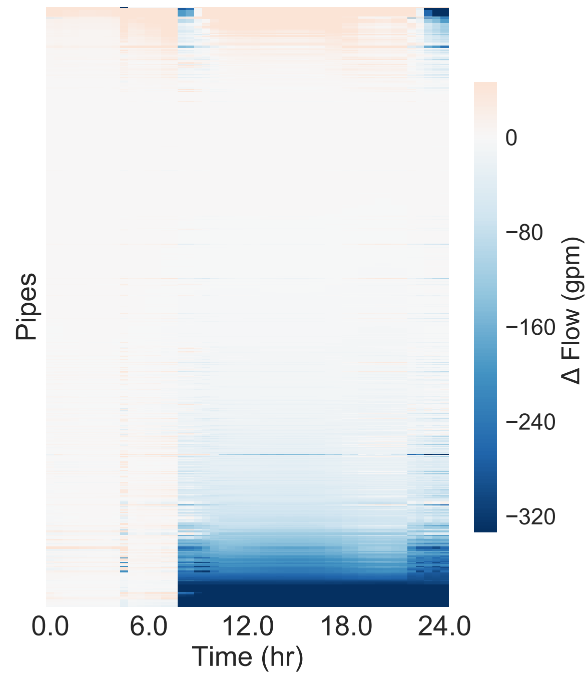


Figure A.14: Distribution of Δ pressure and flow across the Net 6 for each time step under S1 and S2.



(a) S1, Water Pressure



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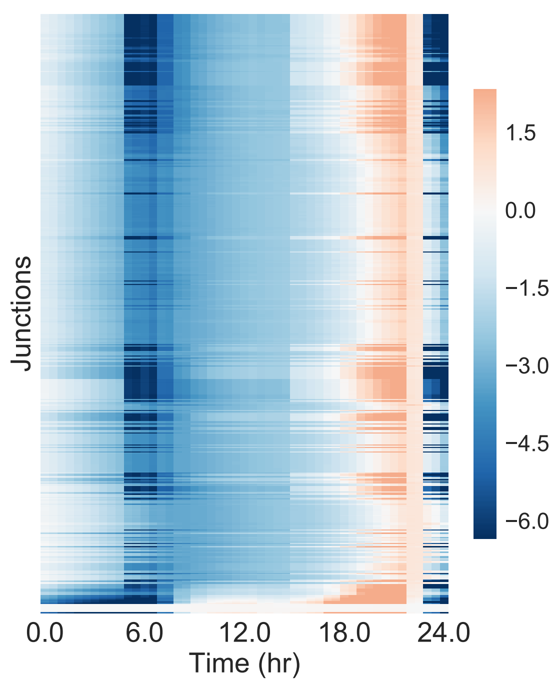
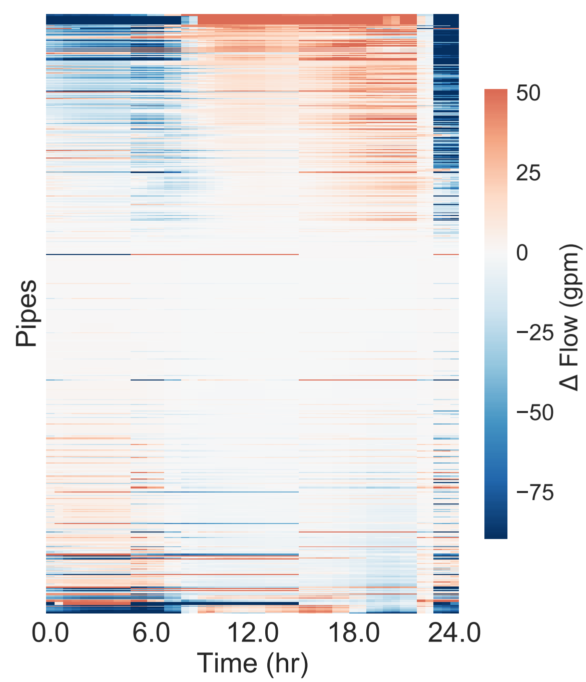


(c) S2, Water Pressure



(d) S2, Flow Rate

Figure A.15: Heat matrices of all Δ pressure and flow distributions in the Net 6 over time under S1 and S2.

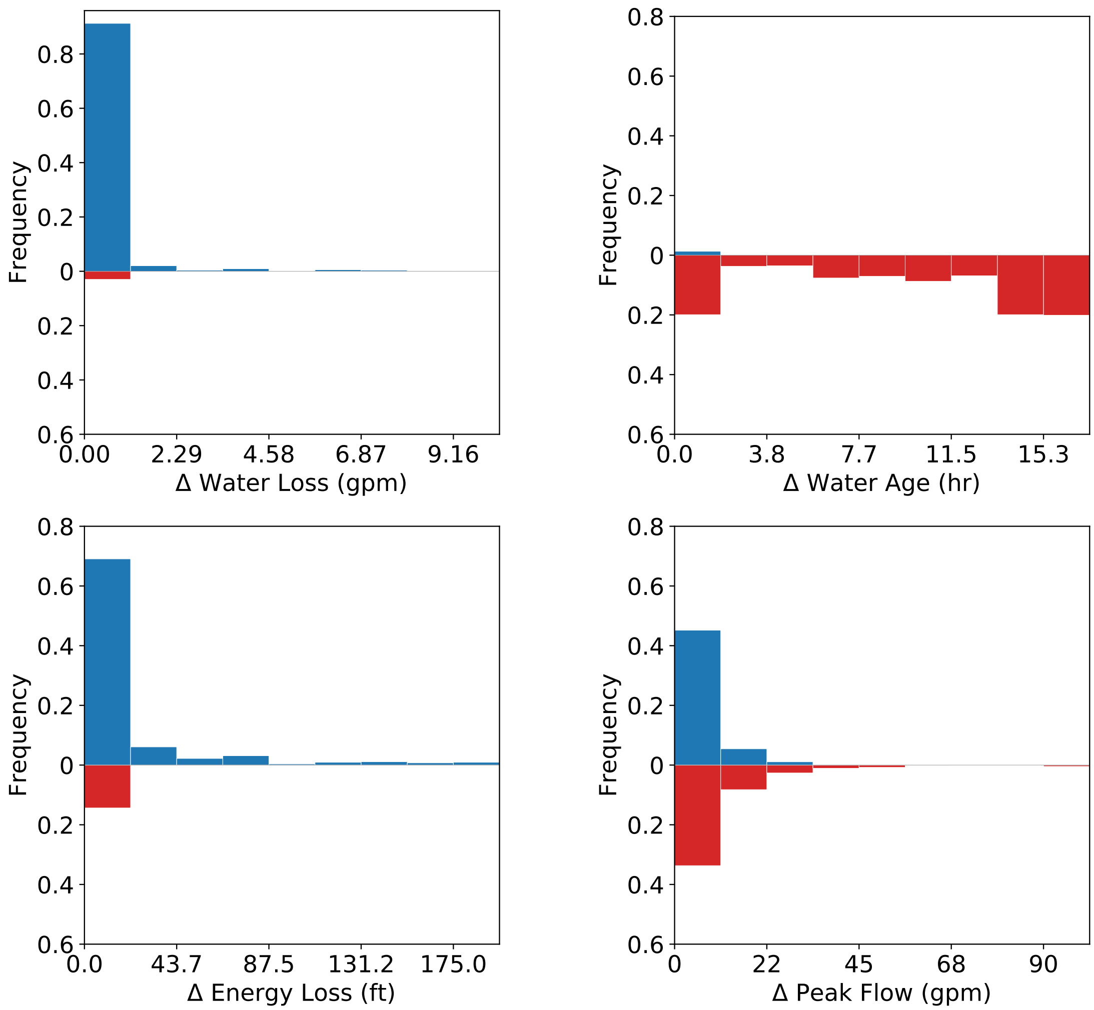


Figure A.16: Histograms of changes in performance metrics for Net 6 under S1.

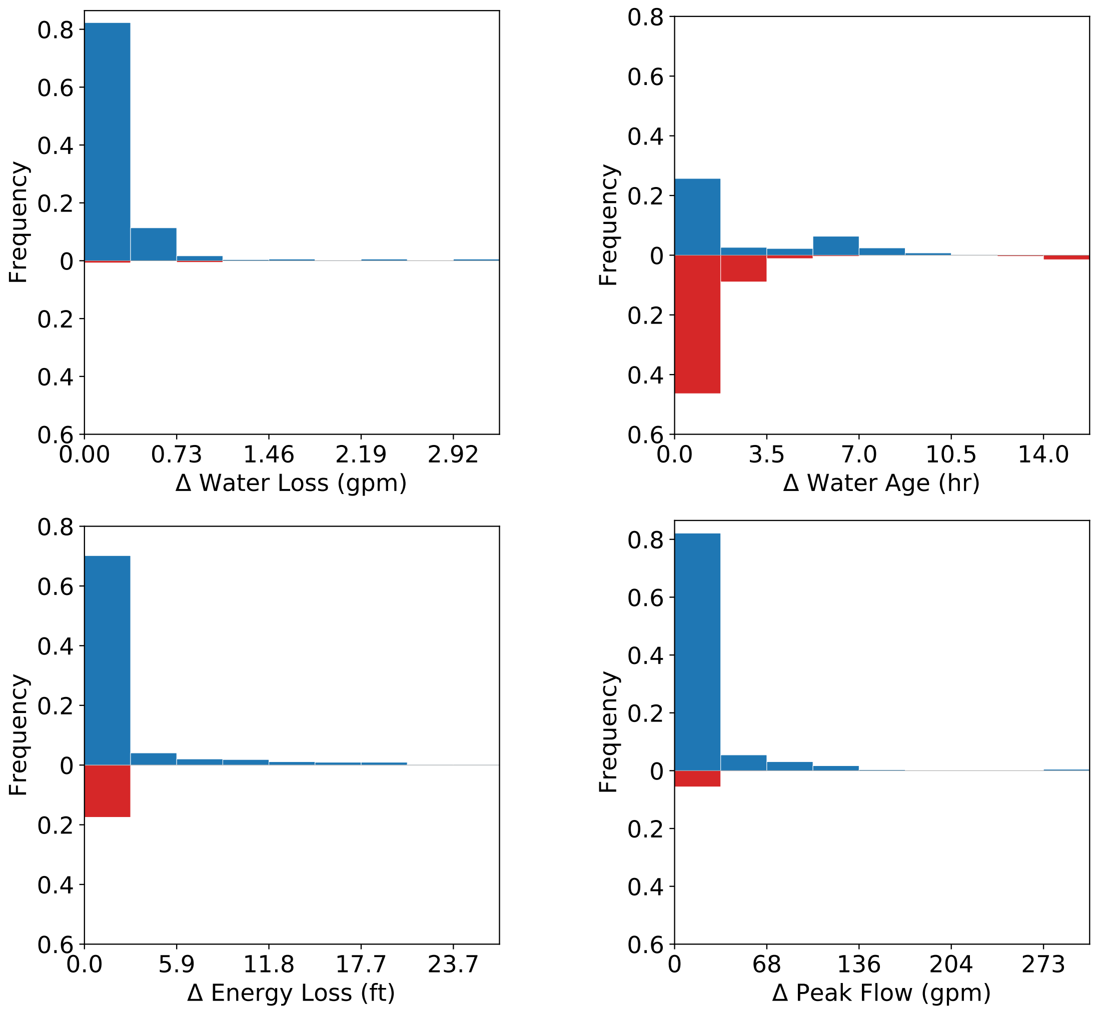
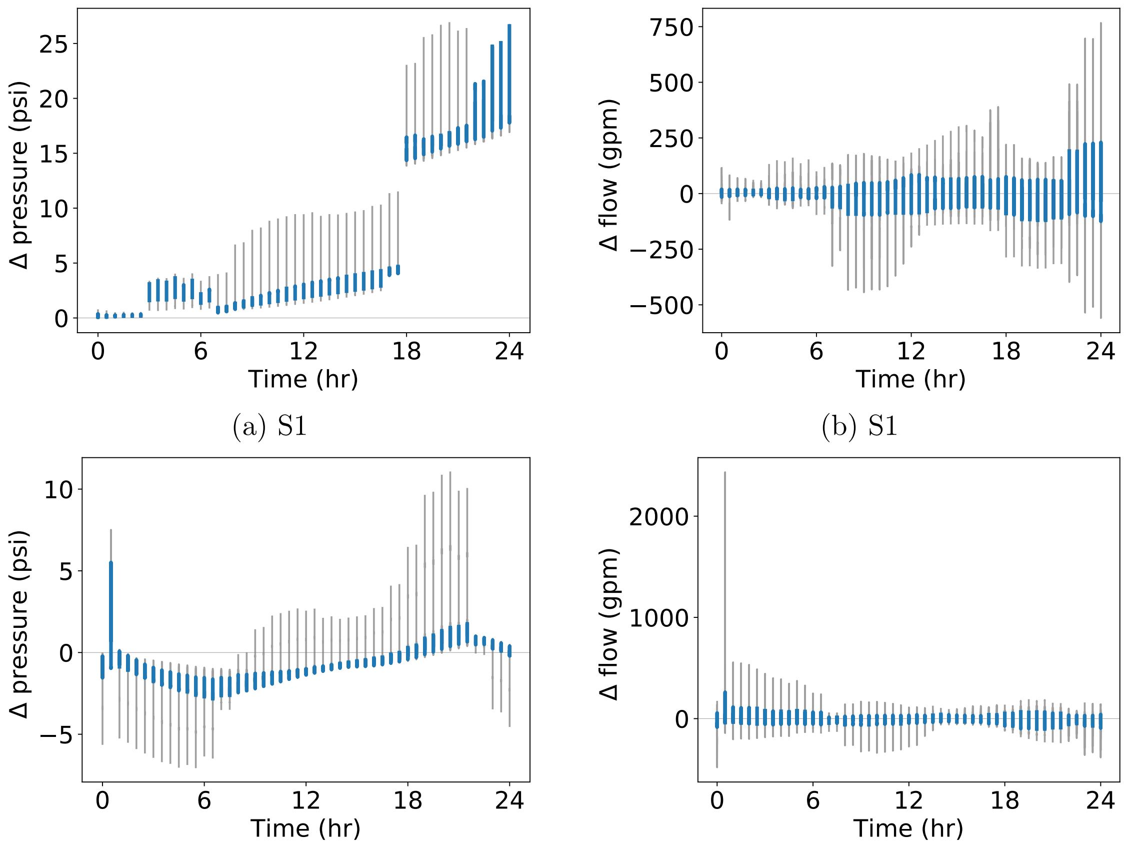


Figure A.17: Histograms of changes in performance metrics for Net 6 under S2.



(a) S1 (b) S1

(c) S2 (d) S2

Figure A.18: Distribution of Δ pressure and flow across the Net 7 for each time step under S1 and S2.

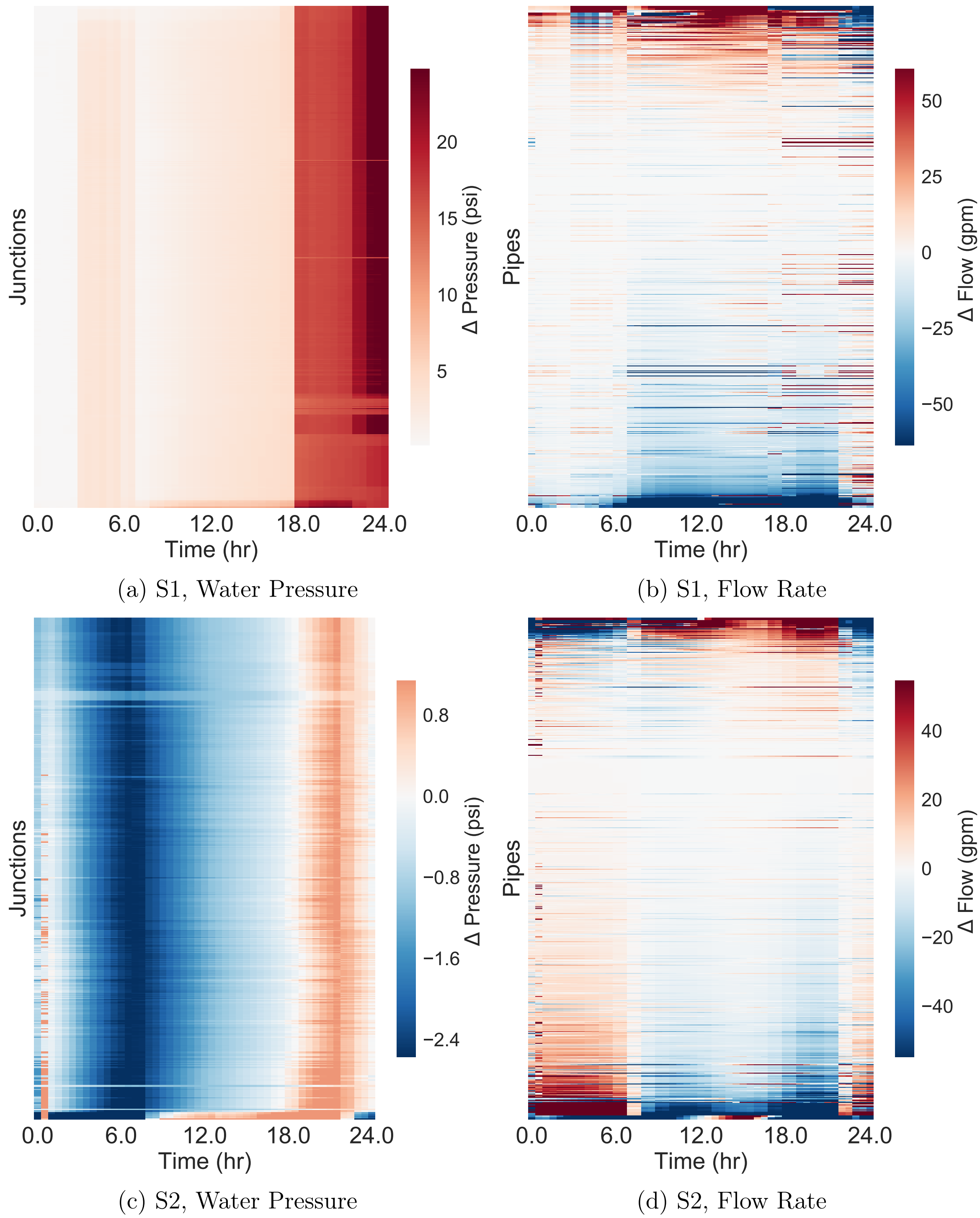


Figure A.19: Heat matrices of all Δ pressure and flow distributions in the Net 7 over time under S1 and S2.

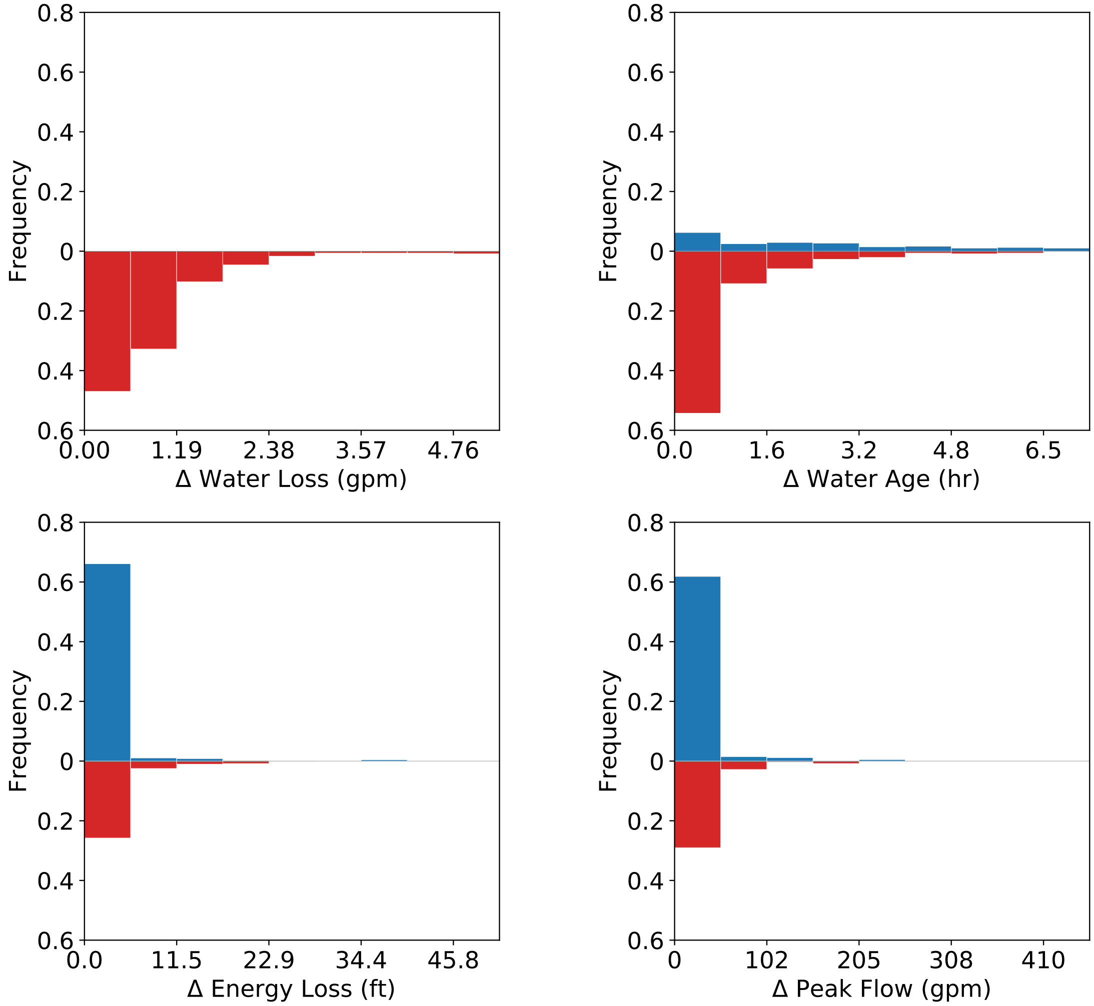


Figure A.20: Histograms of changes in performance metrics for Net 7 under S1.

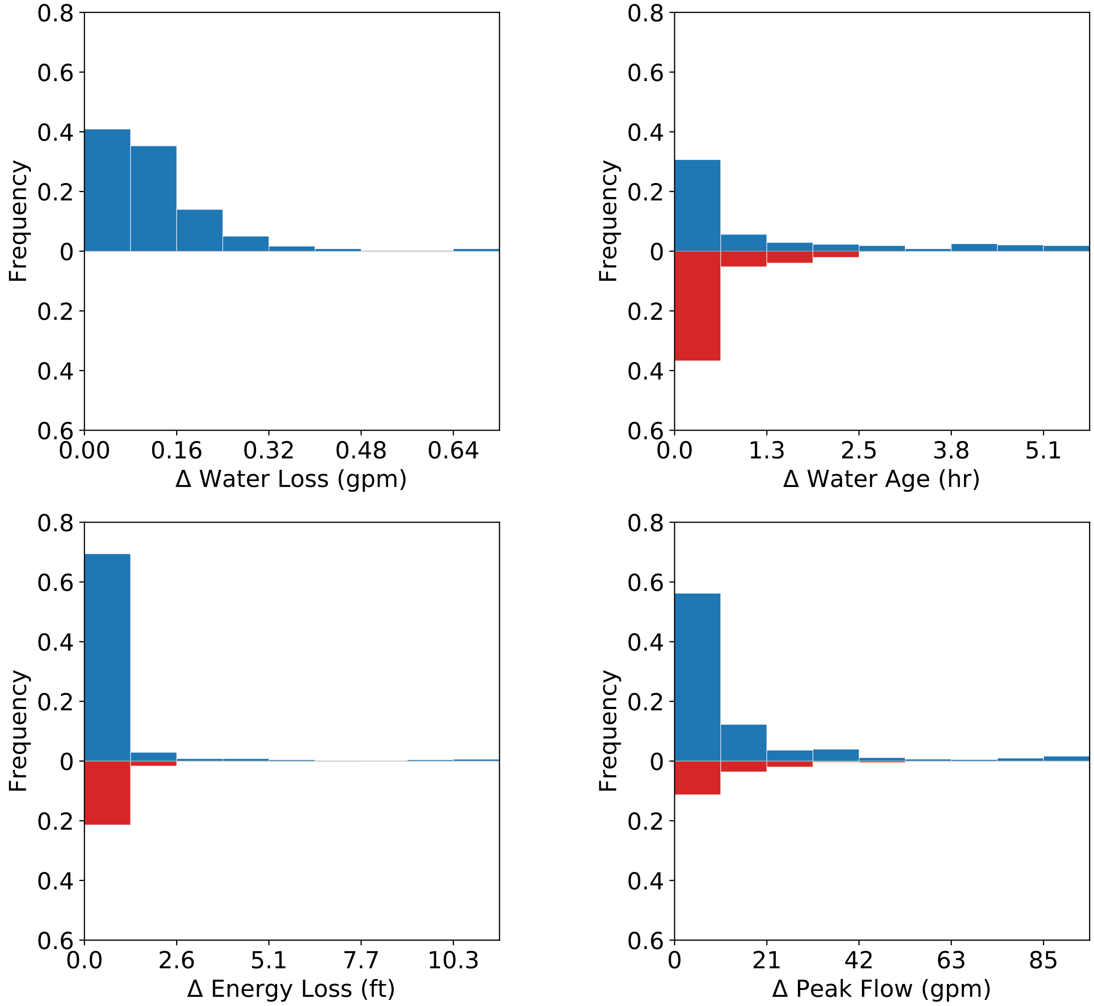
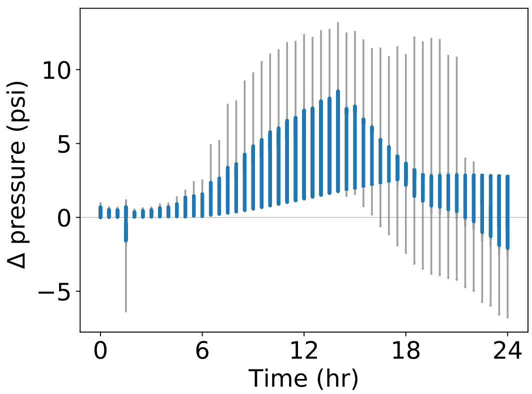
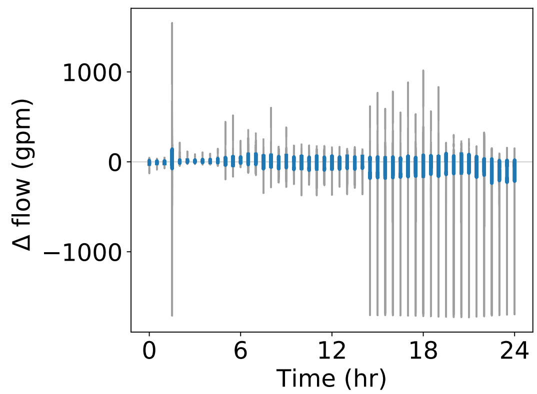


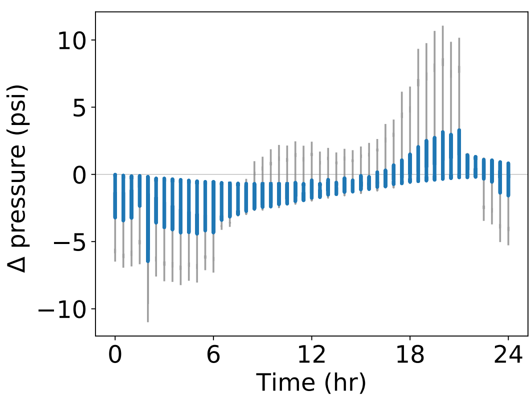
Figure A.21: Histograms of changes in performance metrics for Net 7 under S2.



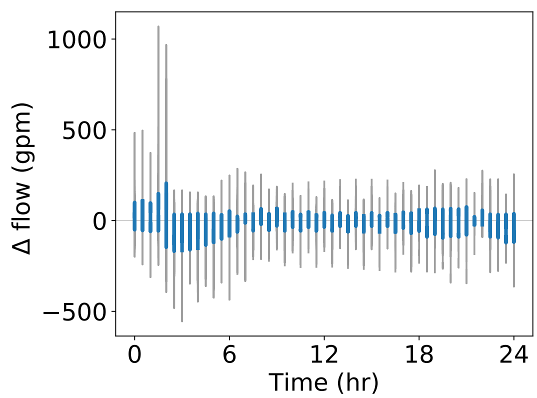
(a) S1



(b) S1

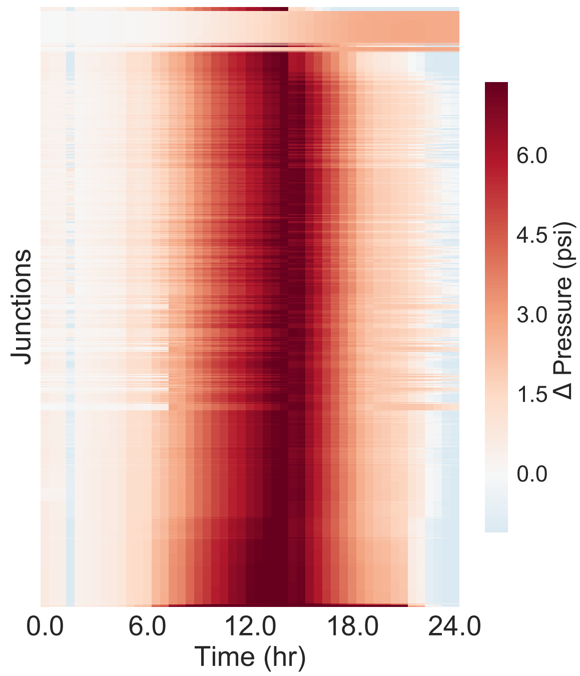


(c) S2

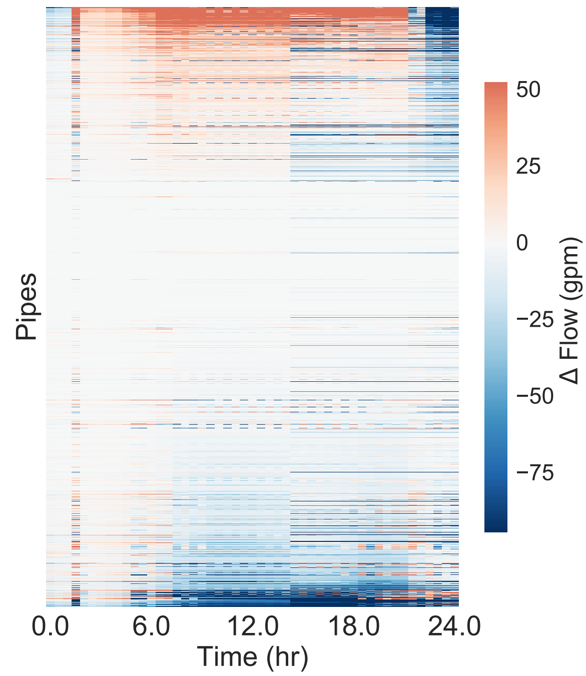


(d) S2

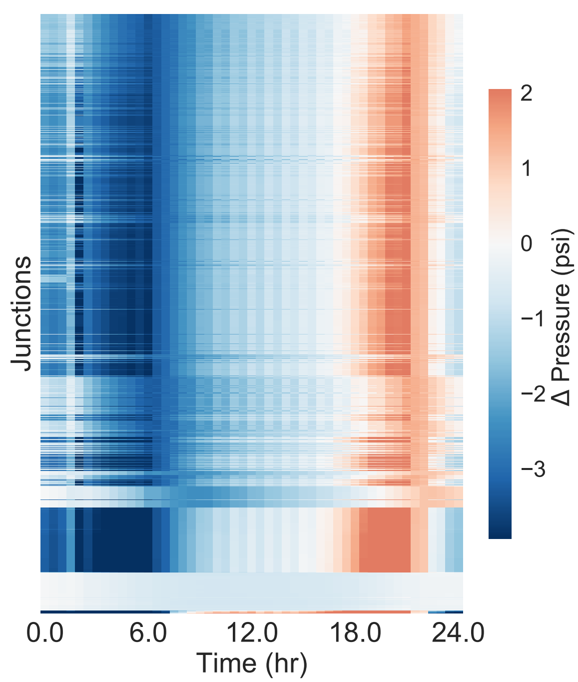
Figure A.22: Distribution of Δ pressure and flow across the Net 8 for each time step under S1 and S2.



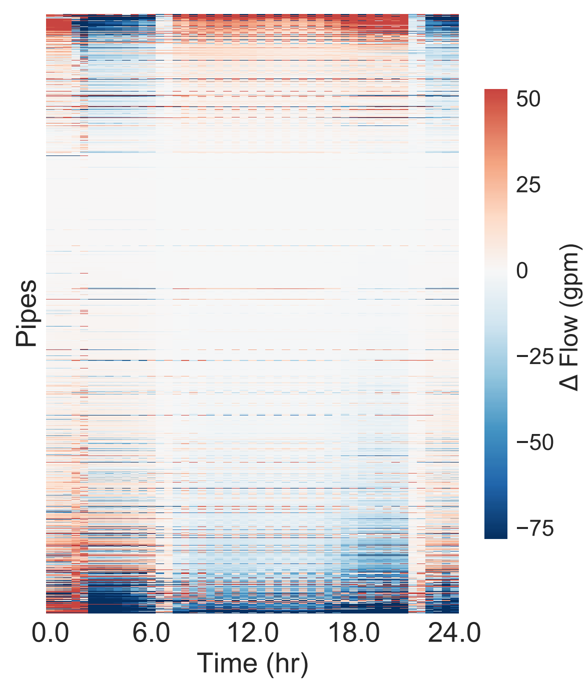
(a) S1, Water Pressure



(b) S1, Flow Rate



(c) S2, Water Pressure



(d) S2, Flow Rate

Figure A.23: Heat matrices of all Δ pressure and flow distributions in the Net 8 over time under S1 and S2.

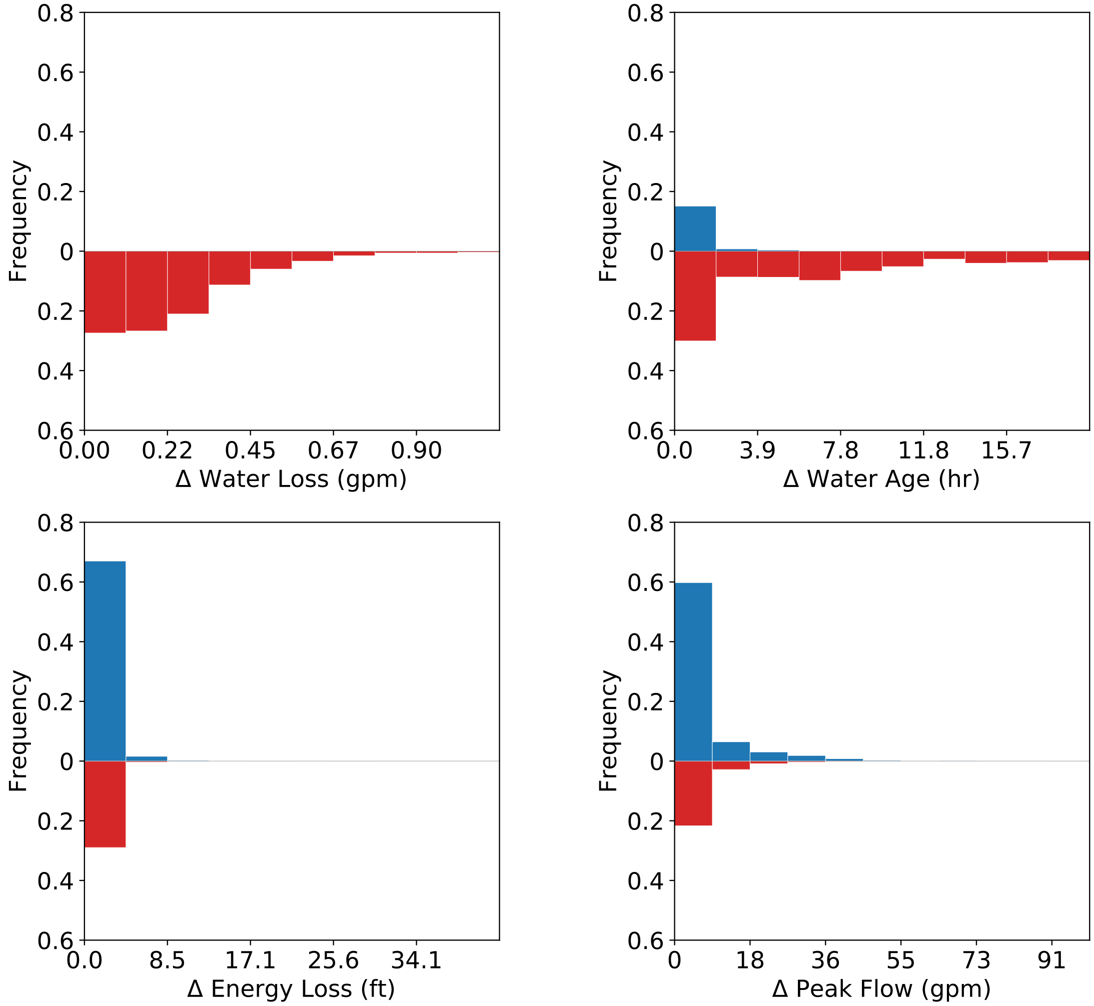


Figure A.24: Histograms of changes in performance metrics for Net 8 under S1.

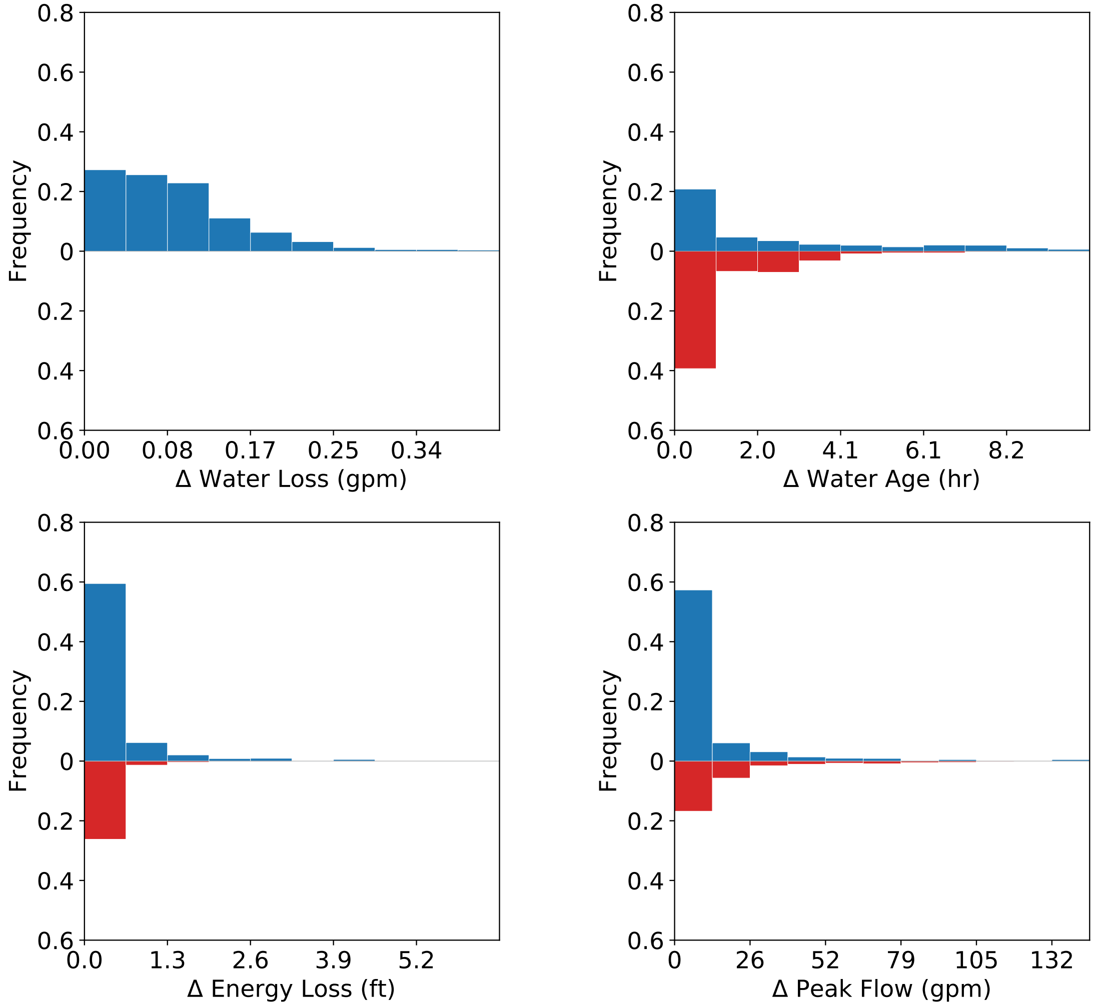


Figure A.25: Histograms of changes in performance metrics for Net 8 under S2.

Appendix B: Network Effects of Evolving Water Demand Patterns

The following included paper to be an oral presentation at the World Environmental and Water Resources Congress 2018 in Minneapolis, Minnesota. (Zhuang and Sela, 2018).

Network Effects of Evolving Water Demand Patterns

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ABSTRACT

Water demand management strategies, such as more efficient end-use technology, alternative water resources, and demand response policies have shown promise in reducing consumption and shifting peak demands. Improving demand estimation through smart metering, as well as the potential savings from implementing various demand management strategies on the household, regional, and national scales, have been studied in literature. However, there is a lack of research on how these evolving water demand patterns affect the performance of water distribution networks on a network-wide scale. In this study, three residential demand patterns were used: 1) standard diurnal, 2) flattened demand, representing the response to economic incentives or technological mechanisms, and 3) reduced demand, which models the response to efficient end-use technology and alternative water sources. The network dynamics associated with the three scenarios were investigated using a hydraulic simulator. Four metrics are suggested to assess the network-wide performance in each scenario: water loss, peak flow, water age, and energy loss. Results from simulations using a real-world network indicated that decreased consumption and variance in demand had a negative or negligible impact on water loss and age, but there is a potential for savings in terms of reduced energy losses. The results highlight the implications on water management and planning from the network infrastructure and utility side.

INTRODUCTION

Water is increasingly discussed as a sensitive resource, and many researchers and decision makers are emphasizing conservation and improving consumption efficiency. Water demand management (DM) strategies targeted at the average person include conservation policies, pricing, efficient technology, and source recovery and reuse. Understanding the relationship between these strategies, water distribution network (WDN) performance, and actual potential savings for utilities can strengthen the case for quicker and widespread implementation of DM or advise decision makers on how to take better advantage of changing water usage behaviors.

The outcome of most consumer-side DM strategies, such as technological, price-based, and policy approaches, is primarily dependent on short and long-term user response. An example of a technological strategy is the installation of water-efficient appliances as indoor or outdoor fixture retrofits. Certain retrofits may impact usage patterns since high-volume indoor fixtures influence total daily household demand, while outdoor water use drives peak demands (Beal and Stewart 2014). With correct use, alternative supply sources such as rainwater and greywater systems can supplement or replace withdrawal from the WDN for outdoor uses, but high initial costs may hinder widespread implementation (Malinowski et al. 2015). Policy-based approaches regulate water use, typically for conservation purposes. Restrictions on outdoor water use due to drought are correlated with decreased residential consumption (Maggioni 2015). Despite the relative inelasticity of water pricing, many studies propose price-based strategies are more cost-effective and enforceable than other conservation strategies, such as restricting outdoor irrigation (Olmstead and Stavins 2007). Due to increased concerns over water availability in the future, it is likely that current and new methods of DM will endure, hopefully leading to savings.

Financial and volumetric water savings can be estimated at the consumer level, based on ideal response or surveys, and be scaled up to determine savings nationwide. However, actual individual use is unknown, except for in localized areas and over short time scales, due to a lack of metering capability. Therefore, demand estimation is largely based on billing records and historical use. Smart metering is gaining popularity as a tool for developing accurate demand patterns. The high-resolution data can be used to quantitatively predict household demand, identify drivers of consumption, and model demand patterns (Cominola et al. 2015). Other methods of demand estimation include generating, then aggregating, demand pulses by end use, and using stochastic processes to predict household demand (Creaco et al. 2017). Creating more accurate patterns reflecting reduced and less-variable demand, due to the implementation of various strategies, may create substantial savings for water providers and impact future operation and management.

To the authors' knowledge, the literature has only briefly addressed the impacts of evolving water-demand patterns on certain aspects of network performance. Hydraulic models using patterns reflecting water efficiency, rainwater harvesting, and greywater systems showed deferred and reduced pipe augmentations for a WDN, indicating improved infrastructure life and capital cost savings (Gurung et al. 2016). Water savings scenarios have also been used to examine the effect of decentralized water supplies on the water quality performance of an existing WDN (Sitzenfrei et al. 2017).

This work studies demand management to determine impacts on network performance and utility-side energy and water cost savings. Two demand scenarios representing evolving consumer behavior and the implementation of DM are considered in this analysis with the following objectives:

1. Evaluate network performance under each scenario using the four metrics of water loss, peak flows, water age, and energy loss
2. Compare each scenario against performance under a nominal pattern, the standard diurnal, which assumes no net change in behavior
3. Study impact on entire network, as well as certain zones within the network

METHODS

Hydraulic analysis was conducted using demand scenarios chosen to determine the effects of changes in water usage on network performance. This study assumes that all consumers within a network exhibit residential-user demand behavior. Table 1 describes the chosen scenarios. Figure 1 is a plot of the corresponding demand pattern for each scenario. Scenario S1 serves as the baseline, therefore the demand pattern is a standard diurnal curve from the American Water Works Association (AWWA 1989), as shown in Figure 1.

Scenario S2 for reduced demand was chosen to investigate the effects of currently prevalent and emerging DM strategies, such as water-efficient technology. The pattern in

Scenario S2 was based on residential smart-metered data collected in a study showing a significant reduction from the traditional demand for households using efficient appliances as well as rainwater and greywater systems (Gurung et al. 2015). The study found peak demands decreased by up to 52% and 64% on the average and peak days, respectively (Gurung et al. 2015). Therefore, to represent a more ambitious conservation scheme where there is widespread adoption of water-efficient appliances as well as source substitution, the demand in Scenario S2 (reduced) is 50% less than Scenario S1 (nominal). The reduced pattern compared to the nominal can be seen in Figure 1**.**

Scenario S3 represents an extreme case where demand can be made steady throughout the day through various DM strategies. Such a scenario with a flattened demand may decrease variations in water release and energy use by the utility, thereby increasing infrastructure life, along with reducing water loss and associated costs.

Table 1. Water Demand Scenarios

Scenario	Description	Pattern Features
S1	Nominal scenario representing business as usual, or no net change in demand behavior	Standard average-day flow diurnal curve
S2	Reduced scenario representing the response to water efficient end-use technology, as well as resource recovery and reuse, which could decrease overall demand and lower peaks	A uniform reduction of 50% from the nominal, such that the total daily demand is 50% less than that of S1
S3	Flattened scenario representing steady demand throughout the day, which could be achieved by economic incentives or decentralized supply sources shifting and reducing demand	Horizontal line where all peaking factors are equal to 1, such that there is no change in the total daily demand from the nominal

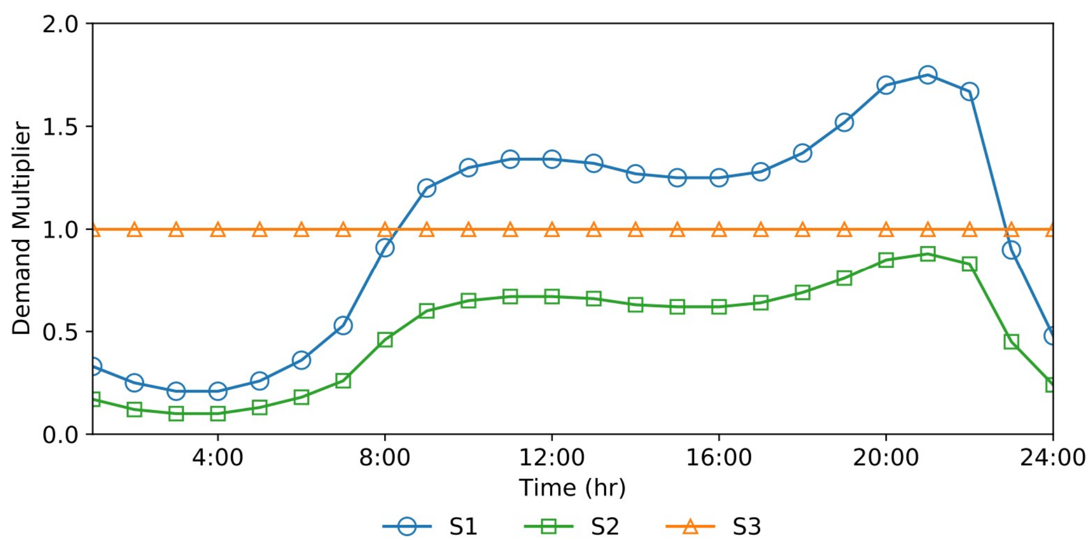


Figure 1. Daily demand patterns for nominal, reduced, and flattened demand scenarios.

To obtain network performance results for comparison between scenarios, hydraulic and quality simulations were run using EPANET2 (Rossman 2000) over an extended period of 24 hours. Performance results were measured using metrics for water loss, peak flow, water age, and energy, and subsequently compared to a nominal scenario. Table 2 contains the equations and descriptions of each metric.

Water loss in a WDN is of concern for utilities due to economic, quality of service, and environmental considerations. In this study, water loss is formulated as the total nodal background leakage *(Mgd)*. Leakage model parameters are $\alpha = 1.5$ for background losses (May 1994; Lambert 2001), and an estimated value of $\beta = 10^{-7}$, which is normally calibrated to a specific WDN for design purposes.

During design and planning, peak flow rates are used to determine adequate pipe capacities. The delivery of clean water is a top priority for water providers and a growing issue nationwide as infrastructure ages. Many characteristics of deteriorating water quality are associated with increased water age, and have potential health impacts (EPA 2002). Metrics for the average peak flow rate *(gpm)* and water age *(hr)* in the WDN are shown in Table 2.

Energy and water production are interlinked. For water utilities, who are major consumers of electricity, possible energy losses and savings in the WDN can have substantial financial and operational impacts. Energy loss *(ft)* is determined using head loss results from the simulation.

Table 2. Network Performance Metrics

Metric	Description
Water Loss	Total background leakage in network, summed from each junction and time step, derived from (Giustolisi et al. 2008)
Peak Flow	Averaged peak flow rate of all pipes from EPANET (Rossman 2000)
Water Age	Averaged water age of all junctions at end of the simulation period from EPANET (Rossman 2000)
Energy Loss	Total frictional head loss in network, where losses in pipes from EPANET (Rossman 2000) are attributed to the incident nodes

RESULTS

Each scenario was applied to a WDN and the performance metric results from the evolving demand scenarios were compared to the nominal. Water distribution network ky2 has 815 nodes, 1124 pipes consisting of approximately 500×10^3 *ft* , one pump, three tanks, and one source. A graph of the real-world network is shown in Figure 2, where the source is represented by a round node. The WDN serves 2.09 million gallons of water daily (Jolly et al. 2014).

Table 3 includes additional network properties. Table 4 contains resulting performance metric values from the simulations of each scenario, as well as the percent differences from the nominal value.

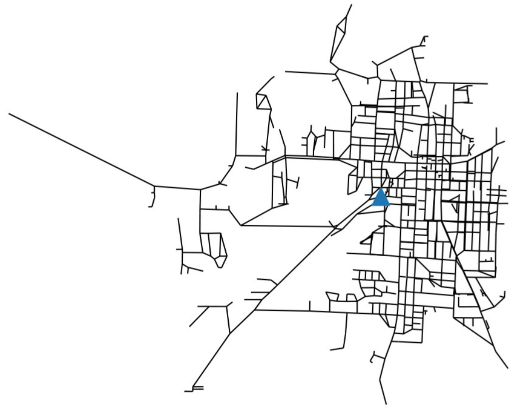


Figure 2. Graph of network ky2

Table 3. Network Properties for Network ky2

Pipe Length *(K-ft)*	Avg. Distance to Source *(K-ft)*	Length/Demand *(K-ft/MGD)*	Demand *(MGD)*	Area *(10^6 ft)*
500	6	239	2.1	480

Table 4. Performance Results for Network ky2

Performance Metrics	Nominal (S1)	Reduced (S2)		Flattened (S3)	
Water Loss *(MGD)*	0.1	0.09	(-13.8%)	0.1	(-0.2%)
Peak Flow *(gpm)*	88	92	(4%)	90	(2%)
Water Age *(hr)*	7	13	(81%)	12	(69%)
Energy Loss *(K-ft)*	268	204	(-24%)	243	(-9%)
Daily Demand *(MGD)*	2.09	1.05		2.09	

Under the nominal scenario (S1), the network experienced daily water loss due to background leakage of 0.10 million gallons, or 5% of the daily demand. The WDN had an average peak flow of 88 *gpm*, an average water age of 7 *hr* after the 24-hour period, and energy loss was 268×10^3 *ft*.

While operating under a reduced demand scheme (S2), the WDN lost 0.09 million gallons of water to leakage, a 13.8% decrease from the nominal (S1), or 9% of the reduced daily demand. The average peak flow increased insignificantly. The mean increase in all pipes was 3.6 *gpm*, with a standard deviation of 38.4 *gpm*, which could be because demand farther from the source still had to be met. The average water age at the end of the simulation period was nearly twice that of S1, an 81% increase, and some nodes experienced increases of up to 18 hours. These high values, seen in Figure 3 could be due to dead spots since total demand in the WDN is much less in this scenario. Figure 3 displays folded histograms for each metric, showing the actual differences in value between the reduced (S2) and nominal (S1) scenarios, where differences were calculated by subtracting values in S1 from those in S2. Figure 4 shows the differences between the flattened (S3) and nominal (S1) scenarios. A value increase from S1 is indicated by red bars, while a value decrease from S1 is blue. For example, in Figure 3, the red bars (increases) were more perceptible than the blue (decreases), indicating an overall increase in water age, which was reaffirmed by the mean differential value of positive 5.9 *hr* displayed in the plot, as well as the overall values and percentages discussed previously and listed in Table 4. The energy loss in the WDN decreased 24% from the nominal.

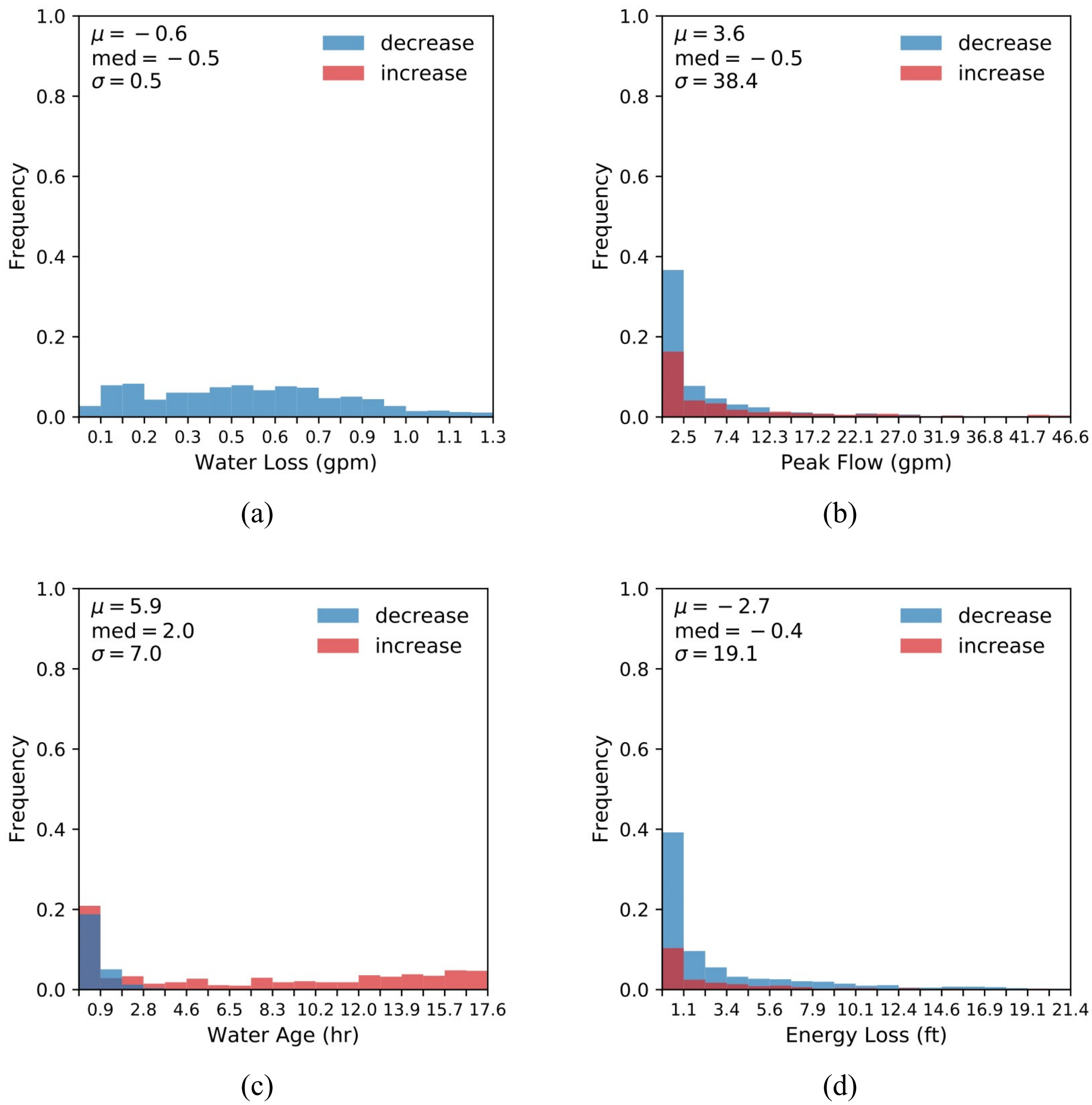
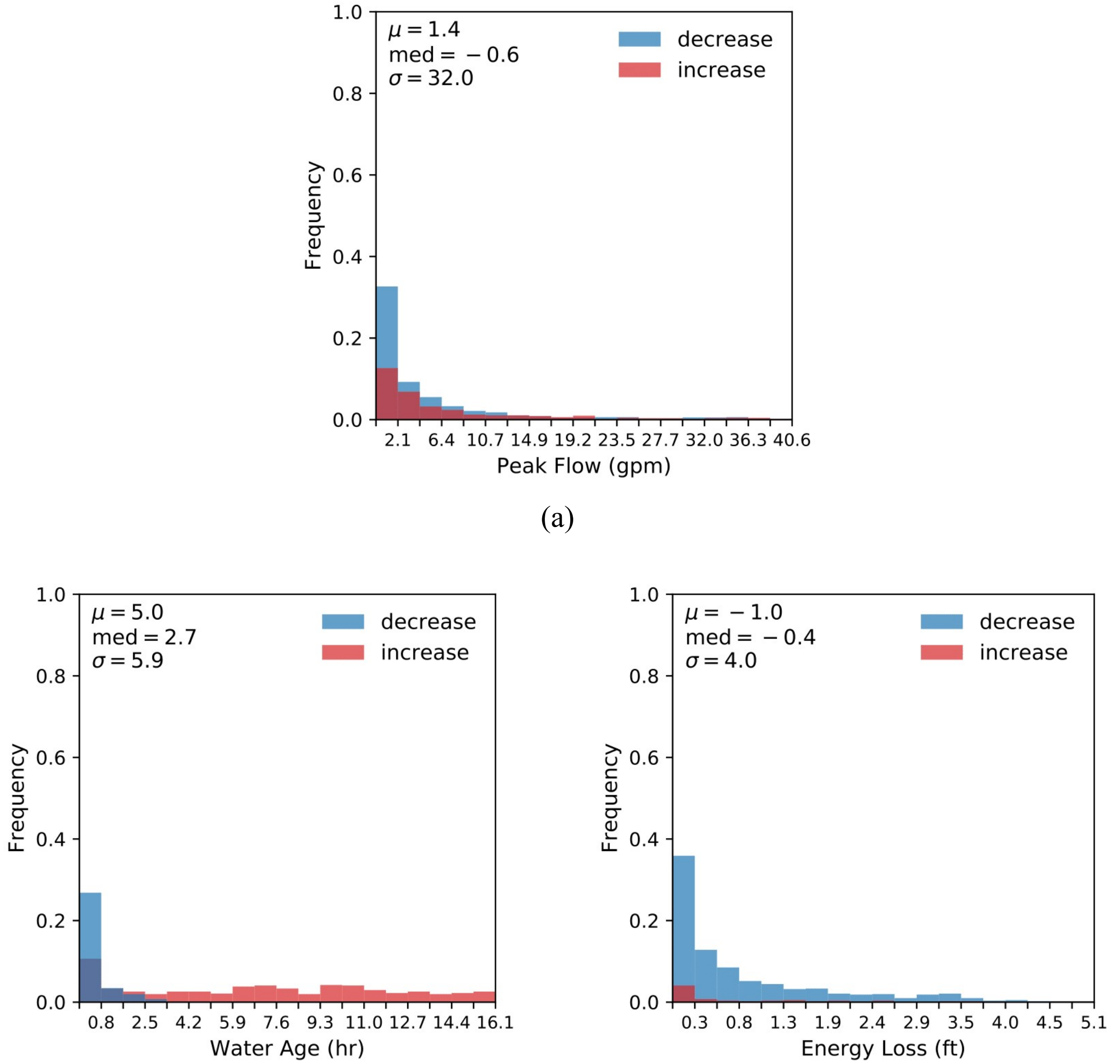


Figure 3. Histograms of differences in performance metric values between reduced (S2) and nominal (S1) scenarios for network ky2.

When demand was flattened (S3), water loss was negligibly different compared to the nominal (S1), at 0.10 million gallons and 5% of total demand. Nodal water losses were very small, on the order of 10^{-2} *gpm*, which was insignificant and could be due to numerical error. Therefore, the histogram of water loss value is not shown in Figure 4. Average peak flow increased slightly, but similar to the reduced scenario (S2), is an insignificant difference compared to the nominal. Also similar to behavior seen in S2, water age increased by 69% from the nominal. The mean increase at the nodes was 5 hours, and some nodes experienced up to a 16 hour increase. Energy loss decreased by 9% from the nominal pattern, which was a smaller change than under the reduced pattern.

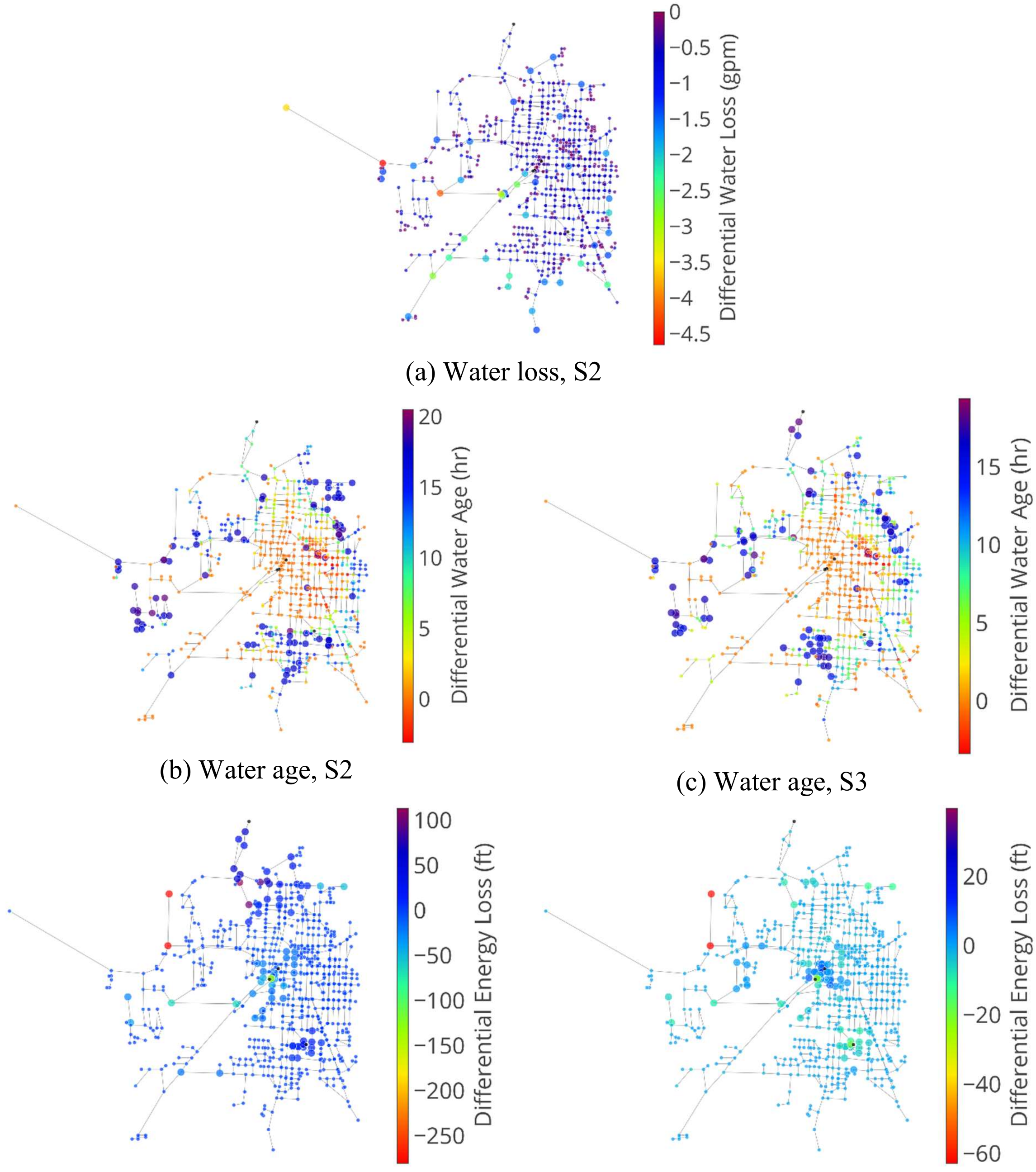


(a)

(b) (c)

Figure 4. Histograms of differences in performance metric values, except water loss, between flattened (S3) and nominal (S1) scenarios for network ky2.

A spatial analysis of differential values for each evolving demand scenario was included to provide insights into what areas of the network were most impacted, so that a utility may adjust service accordingly. The analysis was conducted visually. In this study, water loss, age, and energy loss were all calculated from nodal values. Figure 5 shows color map graphs of the *differential* values from the nominal of each metric. The differential values were calculated by subtracting nominal-scenario results from S2 or S3 results. Colored enlarged nodes have values in the top 5 or 10 percentiles. Under the reduced scenario (S2), the majority of the network experienced small reductions in water losses from the nominal. In Figure 5a, since all nodes in S2 experienced a decrease in water loss from the nominal, the darker purple and blue represents little to no reduction, while the warmer colors indicate a greater reduction. The majority of nodes that saw the greatest reduction in water loss (top 5%) were on the outer edges at the bottom of the graph, as noted by the enlarged nodes. The graph for water loss from the flattened scenario (S3) was not included in Figure 5, or subsequent figures, due to insignificant values. For both scenarios, there was greater degradation in water age as water moved away from the center of the graph (source), except for along the largest main. In Figure 5b-c, the red indicates no change or a slight improvement in age, while colors moving up the scale to dark blue and purple indicate increasing degradation. For energy loss in both scenarios, the same few nodes had extreme reductions in head loss, as seen by the large red nodes on the left in Figure 5d-e. The darker blue and purple nodes represent an increase in energy loss from the nominal, while the other colors indicate a reduction in energy loss. The majority of nodes in both scenarios showed a reduction in energy loss from the nominal. Nodes in the top 10% of differential energy loss values were primarily clustered around the source and tanks.



(a) Water loss, S2

(b) Water age, S2

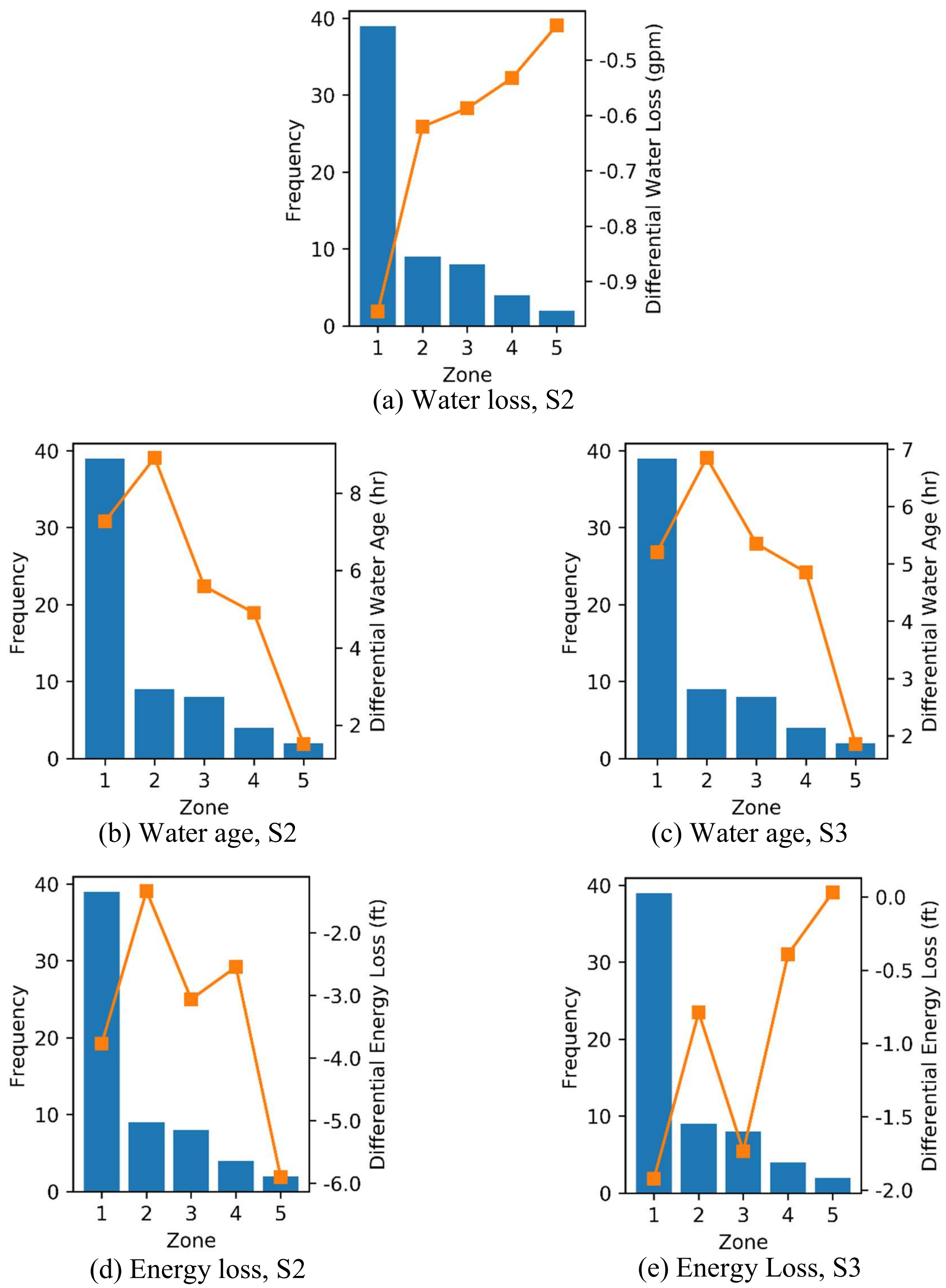
(c) Water age, S3

(d) Energy loss, S2

(e) Energy loss, S3

Figure 5. Graphs of differences from the nominal in performance metric values for S2 (a; b; d) and S3 (c; e) for network ky2.

The WDN was split into five density zones, determined by the number of nodes in a 2000 *ft* × 2000 *ft* gridded area, as seen in Figure 7. Zones 1-5 had densities of less than 10, 20, 30, 40,and 50 nodes per area, respectively. There were 120 density-areas in total. Figure 6 shows plots for *differential* metrics by zone overlaid on a frequency histogram of the zones determined by node. For the reduced scenario, there was a greater reduction in water loss as density decreased, which could be attributed to fewer pipes in the area and less overall demand. In both scenarios, degradation in water age was shown to increase when the area was less dense. For energy loss under the reduced scenario, areas with lower density had a smaller reduction in head loss, and those with a higher density had larger reductions, while the opposite occurred when demand was flattened.



(a) Water loss, S2

(b) Water age, S2

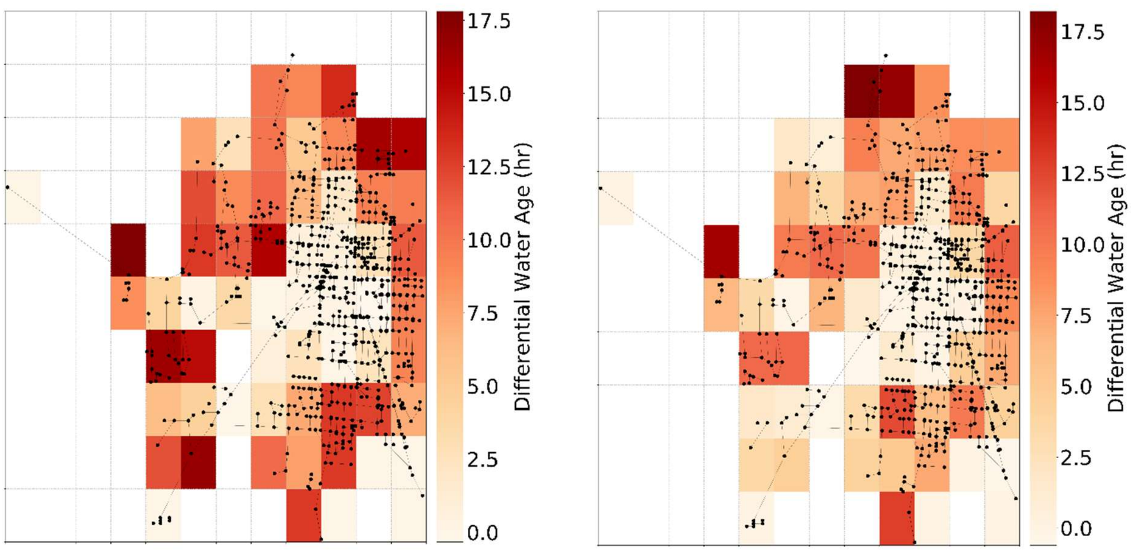
(c) Water age, S3

(d) Energy loss, S2

(e) Energy Loss, S3

Figure 6. Plots of average differences from the nominal in performance metric values per density zone f for S2 (a; b; d) and S3 (c; e) for network ky2.

Figure 7 displays heat maps of the WDN using *differential* age values from the nominal for S2 and S3. A darker coloring indicated a greater degradation in water age under the reduced or flattened scenarios compared to the nominal. A visual examination of the heat maps suggests that degradation increased as water moved away from the source, located near the center of the map as seen in Figure 2. Some visibly denser grids farther from the sources showed higher differences in age from the nominal. The heat maps suggest that topology and other network characteristics may impact how different WDNs behave under different demand scenarios. Additionally, the maps provide insight into what areas of the network require further attention or other solutions under reduced or flattened demand.



(a) Water age, S2 (b) Water age, S3

Figure 7. Heat maps for differences in water age *(hr)* from the nominal for S2 and S3 for network ky2.

SUMMARY AND CONCLUSIONS

The goal of this study was to evaluate network performance under various demand scenarios, with an interest in determining savings for utilities as DM is expanding. Results from using evolving demand patterns showed little to no savings in water loss, which could be due to the demand-driven simulations or operational rules intended for higher demands. Negligible differences in peak flow rates could also indicate the impact of operational rules on performance. Reducing and flattening demands resulted in degraded detention times across the network, which has implications on water quality. Decreases in energy losses indicate energy savings in scenarios where overall demand is reduced, peaks are minimized, and demand throughout the day is less variable. A visual spatial analysis showed that age degradation increased as water move farther from source, compared to the nominal scenario. Additionally, nodes with greater changes in energy loss were clustered near the source and tanks. The results highlight the implications on water management and planning from the network infrastructure and utility side. Water service providers will need to adapt to changing usage behaviors in order to capitalize on energy savings, while maintaining water quality.

This study focused on analysis of a single network. Given the steep reduction in demand, savings were not as great as expected. Exact savings cannot be quantified due to factors that are unobservable in available networks and simulations, such as measurement accuracy, energy and water rates, efficiency of the infrastructure, maintenance needs, detailed user demand and attributes, etc. However, the results reveal insights into network performance under evolving patterns. Further investigation is warranted, including additional networks of various topology and size for comparison. Other considerations may include increased stress on the network due to population growth or migration. Since residential consumers are relatively similar and homogeneous in behavior, this study assumed only residential demand in the WDN. Future work to include industrial and commercial users and patterns would be worthwhile to better understand the effects of demand management on real-world network performance.

Appendix C: Python Script

The python 2 script written for this project can be found at `https://bitbucket.org/jgz8av/demand-scenarios`.

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